Simulating Human Behaviour in Social-Ecological Systems:

Farmers’ Adoption of Agricultural Innovations

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Zusammenfassung

Der Agrarsektor steht vor der großen Herausforderung, ausreichend Nahrungsmittel für die wachsende Weltbevölkerung bereitzustellen. Zudem steigt der Druck auf die landwirtschaftlichen Produktionssysteme aufgrund prosperierender Volkswirtschaften und zunehmender Bodendegradation, während der Klimawandel ihre Produktivität beeinträchtigt. Einen vielversprechenden Weg zur Bewältigung dieser aktuellen Herausforderungen stellt die Wende zur nachhaltigen Landwirtschaft dar. Nachhaltige landwirtschaftliche Praktiken wie Agroforstwirtschaft können sowohl zur Ernährungssicherung als auch zum Klimaschutz und Erhalt von Ökosystemleistungen beitragen. Trotz dieser Vorteile ist die Implementierung von Agroforstsystemen unter Kleinbäuer*innen in bestimmten Regionen sehr niedrig. Um eine höhere Umsetzungsrate von Agroforstpraktiken zu erzielen, sind Maßnahmen erforderlich, welche Kleinbäuer*innen bei der Implementierung unterstützen. Damit politische Entscheidungstragende entsprechende Maßnahmen erfolgreich konzipieren, müssen sie die Auswirkungen solcher Maßnahmen abschätzen können. Dies setzt voraus, dass sie die Präferenzen der Kleinbäuer*innen und die Gründe für ihre Entscheidungen verstehen.

Die Implementierung nachhaltiger landwirtschaftlicher Praktiken durch Kleinbäuer*innen und die zugrundeliegenden Entscheidungsprozesse stehen im Mittelpunkt dieser Dissertation. Das übergeordnete Ziel der Arbeit besteht darin, die Entwicklung und Umsetzung wirksamer Politikinstrumente voranzutreiben und dadurch Kleinbäuer*innen bei der Implementierung von innovativen landwirtschaftlichen Praktiken zu unterstützen. Die spezifischen Ziele der Arbeit sind (1) effiziente Strategien zur Verbreitung von landwirtschaftlichem Wissen in sozialen Netzwerken zu identifizieren, (2) verschiedene Verhaltenstheorien gegenüberzustellen, um Implementierungsentscheidungen besser erklären zu können, (3) intrinsische Motivationsfaktoren basierend auf der Theorie des geplanten Verhaltens zu identifizieren und die Wirksamkeit von nicht-ökonomischen Politikinterventionen ausgerichtet auf diese intrinsischen Motivationsfaktoren zu evaluieren und (4) die sozialökologischen Folgen der Implementierungsentscheidungen unter verschiedenen Klimaszenarien zu analysieren. Diese Arbeit gliedert sich entsprechend der spezifischen Ziele in vier Aufsätze, die sich auf unterschiedliche Stufen des Innovations-Entscheidungsprozesses fokussieren. Während sich der erste Aufsatz auf landwirtschaftliche Innovationen im Allgemeinen bezieht, konzentrieren sich die nachfolgenden Aufsätze auf Agroforstwirtschaft als nachhaltige landwirtschaftliche Praktiken.

Als primäre Methodik werden in dieser Arbeit agentenbasierte Simulationsmodelle angewandt. Agentenbasierte Modelle simulieren sozialökologische Systeme auf der Basis von autonomen Agenten, die heterogene Eigenschaften, Ziele und Verhaltensregeln aufweisen können. Ausgehend von den Aktionen und Interaktionen der Agenten auf der Mikroebene können agentenbasierte Modelle Dynamiken auf der Systemebene simulieren. Solche Modelle sind für die Analyse landwirtschaftlicher Implementierungsentscheidungen gut geeignet, da sie individuelle Entscheidungsprozesse explizit darstellen und Interaktionen zwischen Menschen sowie Wechselbeziehungen zwischen Menschen und Umwelt im Laufe der Zeit berücksichtigen können. Zudem ermöglichen sie Vorhersagen unter hypothetischen Szenarien. Ökonometrische Instrumente wie binäre Regressions- und Strukturgleichungsmodelle können Input für agentenbasierte Modelle liefern und wurden in dieser Arbeit ebenfalls als Methodik angewandt. Zudem wurden die Simulationsergebnisse mittels statistischer Methoden wie der Varianzanalyse ausgewertet.

Die für diese Arbeit entwickelten agentenbasierten Simulationsmodelle beziehen sich auf unterschiedliche Forschungsregionen und Datensätze. Das Modell des ersten Aufsatzes verwendet sozioökonomische Umfragedaten und Navigationssatellitendaten zur Positionsbestimmung von 264 Haushalten aus einer ländlichen Region in Sambia. Diese Daten wurden während eines regionalen Zensus im Jahr 2018 erhoben. Die Input-Daten für das agentenbasierte Modell des zweiten Aufsatzes umfassen Umfragedaten von 145 Kleinbäuer*innen aus einer ländlichen Region Ruandas aus dem Jahr 2020. Von diesen Befragten nahmen 72 zufällig ausgewählte Kleinbäuer*innen an einem Rollenspiel zur Validierung des Modells teil. Der dritte Aufsatz nutzt eine modifizierte Form dieses zweiten Modells und basiert daher auf den gleichen Input-Daten. Das agentenbasierte Modell für den vierten Aufsatz verwendet Daten, die in einer abgelegenen Region Indonesiens erhoben wurden. Dabei liefert eine sozioökonomische Befragung von 139 Haushalten aus dem Jahr 2014 die primäre Datengrundlage. Darüber hinaus verwendet das Modell Fernerkundungs- und Geoinformationssystemdaten sowie Biodiversitätsindikatoren aus der Forschungsregion. Insgesamt konzentriert sich diese Arbeit auf ländliche Gebiete in Entwicklungsländern in Afrika und Asien. In diesen Regionen hängt der Lebensunterhalt vieler Menschen erheblich von der Landwirtschaft ab. Diese Kleinbäuer*innen sind landwirtschaftlichen Risiken in besonderem Maße ausgesetzt, da sie in Gebieten leben, in denen der Klimawandel voraussichtlich die stärksten Auswirkungen haben wird und die Ernährungssicherung besonders gefährdet ist. Daher ist die Implementierung nachhaltiger landwirtschaftlicher Praktiken wie Agroforstwirtschaft in diesen Regionen besonders wichtig.

Das erste Kapitel dieser Arbeit führt in das Thema ein. Die darauffolgenden Kapitel beinhalten die einzelnen Aufsätze. Der erste Aufsatz in Kapitel 2 untersucht, welchen Personengruppen politische Entscheidungstragende Informationen zuerst bereitstellen sollten, damit sich landwirtschaftliches Wissen möglichst schnell und weit innerhalb eines sozialen Netzwerks verbreitet. Die Simulationsergebnisse zeigen, dass Informationen unter den Kleinbäuer*innen am schnellsten weitergegeben werden, wenn politische Entscheidungstragende Personen mit der höchsten Anzahl an direkten Kontakten informieren. Auch wenn Menschen, die am häufigsten auf dem kürzesten Pfad zwischen zwei anderen Personen im Netzwerk positioniert sind, oder Dorfoberhäupter die Informationen zuerst erhalten, verbreitet sich das Wissen relativ schnell. Eine erhöhte Anzahl an Personen, welche die Informationen unmittelbar zu Beginn erhalten, verbessert die Wissensverbreitung, wobei jedoch der Grenznutzen zusätzlicher initial Informierter abnimmt. Die Simulationen bestätigten, dass die Interaktionseffekte zwischen dem Auswahlkriterium und der Anzahl anfangs informierter Personen den Wissenstransfer erheblich beeinflussen. Insgesamt verdeutlichen die Ergebnisse, dass eine Wissenstransferstrategie sowohl das Auswahlkriterium als auch die Anzahl der zuerst Informierten berücksichtigten sollte, um Informationen schnell und weit innerhalb eines Netzwerks zu verbreiten.

Kapitel 3 vergleicht unterschiedliche verhaltenstheoretische Ansätze, um die Entscheidungsfindung von Kleinbäuer*innen zu erklären. Das dabei betrachtete Verhalten bezieht sich auf die Entscheidung, innovative Agroforstsysteme zu implementieren. Die Ergebnisse zeigen, dass die prognostizierte Implementierung abhängig von dem für die Simulationen gewählten Verhaltensansatz variiert. Verglichen mit einem zur Validierung durchgeführten Rollenspiel überschätzen die prognostizierten Entscheidungen, deren Simulation auf dem ökonometrischen Ansatz basiert, das Adoptionsverhalten leicht. Die Repräsentation von Kleinbäuer*innen als vollständig rationale Gewinn-Maximierer überschätzt die Implementierung ebenfalls, während die „satisficing"-Heuristik und der Entscheidungsbaum als Theorien der begrenzten Rationalität die Implementierung unterschätzen. Die Resultate weisen die höchste Validität auf, wenn die simulierten Entscheidungen auf der Theorie des geplanten Verhaltens basieren. Diese Ergebnisse zeigen, dass eine intrinsische Motivation in Bezug auf den Biodiversitätserhalt sowie Umwelt- und

Klimaschutz relevant für die persönliche Einstellung ist und die daraus resultierende Intention, Agroforstsysteme zu implementieren, erheblich beeinflusst.

Kapitel 4 identifiziert intrinsische Motivationsfaktoren gemäß der Theorie des geplanten Verhaltens und evaluiert darauf aufbauende verhaltensbasierte Politikmaßnahmen, um die Implementierung von Agroforstsystemen mit unterschiedlichen Baumarten zu fördern. Ein Strukturgleichungsmodell zeigt, dass die individuelle Einstellung, subjektive Norm und die wahrgenommene Verhaltenskontrolle der Theorie des geplanten Verhaltens entsprechend die Intention der Kleinbäuer*innen, Agroforstsysteme zu implementieren, beeinflussen. Auf diesen Ergebnissen aufbauend werden drei Interventionen getestet, um diese intrinsischen Motivationsfaktoren stärken zu können. Laut den Simulationsergebnissen wird die Intention der Kleinbäuer*innen, Agroforstsysteme zu implementieren, am stärksten erhöht, wenn eine Informationskampagne das Bewusstsein für die Vorteile des landwirtschaftlichen Systems fördert und sich somit positiv auf die individuelle Einstellung auswirkt. Auch die Verbreitung von Informationen bezüglich der Erwartungshaltung wichtiger Bezugspersonen der Kleinbäuer*innen zur Verstärkung von subjektiven Normen erhöht die Intentionen. Eine weitere wirksame Maßnahme ist die Durchführung von Schulungen, um die wahrgenommene Kontrolle über das Verhalten zu verbessern. Trotz der positiven Auswirkungen der drei Interventionen sind die Effekte auf die Intentionen der Kleinbäuer*innen eher gering. Um den Erfolg dieser Maßnahmen zu maximieren, sollten die Interventionen kombiniert werden. Insgesamt zeigen die Ergebnisse, dass intrinsische Motivationsfaktoren Implementierungsentscheidungen wesentlich beeinflussen. Folglich haben verhaltensbasierte Politikinstrumente ausgerichtet auf diese intrinsischen Motivationsfaktoren Potenzial, landwirtschaftliche Implementierungsabsichten zu stärken, und bieten eine Alternative zu finanziellen Anreizen.

In Kapitel 5 liegt der Fokus auf den Folgen für Mensch und Umwelt, welche durch die Implementierung von Agroforstsystemen ausgelöst werden. Laut den Simulationsergebnissen sind die Kleinbäuer*innen bereit, Agroforstsysteme zu implementieren. Dadurch steigern und diversifizieren sie ihr Einkommen verglichen mit einem Szenario ohne Agroforstwirtschaft, wie die Ergebnisse zeigen. Zu den ökologischen Vorteilen der Agroforstwirtschaft gehören gesteigerte Kohlenstoffbindung durch zusätzliche Biomasse von Bäumen und höhere biologische Vielfalt. Diese positiven Auswirkungen verstärken sich im Laufe der Zeit. Das Simulationsszenario mit steigenden Temperaturen verdeutlicht, dass Kleinbäuer*innen

Agroforstsysteme als Strategie nutzen, um die negativen Konsequenzen des Klimawandels zu bewältigen. Obwohl sich der Klimawandel in beiden Szenarien negativ auf die Biodiversität auswirkt, ist die biologische Vielfalt gemäß der Simulationsergebnisse deutlich höher, wenn die Kleinbäuer*innen Agroforstsysteme implementieren als wenn sie die traditionellen landwirtschaftlichen Produktionssysteme beibehalten. Insgesamt hebt das fünfte Kapitel die vielfältigen Vorteile hervor, die die Einführung von Agroforstwirtschaft auch langfristig mit sich bringt, und dass Mensch und Natur gerade in Anbetracht des Klimawandels von solchen Systemen profitieren können.

Stichworte: Landwirtschaftliche Innovationen; Agroforstsysteme; Adoption von Innovationen; Entscheidungsfindung; Agentenbasierte Modellierung

Abstract

The agricultural sector faces major challenges to produce sufficient food for the world's rising population. As economies grow and land resources degrade, the pressure on global food production systems intensifies. Additionally, climate change reduces agricultural productivity. To address these challenges, a transformation towards sustainable agriculture offers a promising opportunity. Sustainable agricultural practices such as agroforestry can contribute to advance food security, mitigate climate change, and conserve ecosystem services. Despite these benefits, small-scale farmers' uptake of these practices can be very low in certain regions. Consequently, interventions are required that support farmers' implementation and raise low adoption rates. To design effective interventions, policy-makers need to be able to assess the impact of potential measures. Therefore, they must understand the preferences and motivational drivers of farmers' adoption decisions.

Small-scale farmers' adoption of sustainable agricultural practices and the underlying decision-processes constitute the core of this thesis. Overall, the thesis aims to support policy-makers in developing and implementing effective measures that encourage farmers to adopt innovative sustainable practices. The specific objectives are (1) to identify efficient information seeding strategies to disseminate agricultural knowledge within social networks, (2) compare common behavioural approaches to explain farmers' adoption decisions, (3) identify intrinsic drivers based on the Theory of Planned Behaviour and evaluate the effectiveness of non-economic policy interventions targeting intrinsic motivational factors, and (4) assess the interrelated human-environmental consequences of farmers' adoption decisions under different climate scenarios. To investigate these research objectives, the thesis consists of four essays, which address different stages across the innovation-decision process. Whereas the first essay focuses on agricultural innovations in general, the subsequent essays are applied to innovative agroforestry systems as sustainable agricultural practices.

As the main methodology, the thesis uses agent-based simulation modelling. Agent-based models represent social-ecological systems based on autonomous agents, which can have heterogenous characteristics, goals, and behavioural rules. While simulating agents' actions and interactions on the micro-level, this bottom-up method also computes emerging system-level dynamics. Such simulation models are particularly well suited to examine farmers' adoption decisions because they can explicitly incorporate individual decision-making and account for human-environmental and human-human interrelations over time. Furthermore,

they can provide predictions under hypothetical scenarios. Economic tools such as binary regression and structural equation models can provide input for agent-based models and have been applied as methodologies in this thesis as well. Furthermore, the simulation results were assessed via statistical methods such as Analysis of Variance (ANOVA).

The agent-based simulation models developed for the four essays of this thesis are applied to distinct regions and use different datasets. The first essay's model uses socioeconomic survey and Global Positioning System data from 264 households, collected in rural Zambia during a regional census in 2018. Input for the second essay includes survey data from 145 rural Rwandan small-scale farmers, collected in 2020. Of the respondents, 72 farmers were randomly selected to participate in a role-playing game to validate the agent-based model. The third essay is based on a modified version of this second agent-based model and uses the same input data. The fourth agent-based model is applied to a remote region in Indonesia. It uses socioeconomic survey data from 139 households from 2014 as input. In addition, remote sensing and Geographic Information System data as well as biodiversity indicators from the study region are used in this model. Overall, this thesis focuses on rural areas in developing countries in Africa and Asia. In these regions, many people heavily rely on agriculture for their livelihoods. These farmers are particularly vulnerable towards agricultural risks because they live in areas where climate change is expected to have the most severe impacts and food security is particularly jeopardized. Hence, the implementation of sustainable agricultural practices such as agroforestry is especially important in these regions.

The first chapter of this thesis introduces the topic. The following chapters contain the different essays. The first essay in chapter 2 investigates how the selection of farmers who receive a particular information first ("seeds") affects knowledge dissemination within a social network. The simulation results demonstrate that initially informing farmers with most direct contacts in the network leads to the fastest diffusion within the community. Also selecting farmers who are most frequently positioned on the shortest path between two other persons in the network or choosing the village heads as seeds has significant diffusion potential. Increasing the number of seeds improves information spread, but the marginal effects of additional seeds decline. The simulations confirm that the interaction effects between seed selection criterion and set size significantly impact knowledge spread. Thus, the results of the first essay call for seeding strategies that consider both the seed selection criterion and the seed number to achieve fast and widespread information diffusion.

Chapter 3 compares common behavioural approaches to explain farmers' decision-making regarding their adoption of innovative agroforestry systems. The opposed approaches include discounted and non-discounted profit-maximization (perfect rationality theory), "satisficing" and fast and frugal decision tree heuristics (theory of bounded rationality), the Theory of Planned Behaviour (psychological theory), an econometric approach, and random decision-making. The results show that predicted adoption rates vary depending on the behavioural approach assumed during the simulations. Compared with a role-playing game conducted for validation, the implementation rates simulated based on the econometric approach slightly overestimate adoption behaviour. Representing farmers as fully rational profit maximisers overestimates implementation as well, whereas the fast and frugal decision tree and "satisficing" heuristic as theories of bounded rationality underestimate adoption. Highest validity is achieved if farmers' decisions are simulated based on the Theory of Planned Behaviour. These results indicate that intrinsic motivation with respect to the environment, climate change mitigation, and biodiversity conservation forms farmers' attitude and consequently strongly influences their intention to adopt agroforestry.

Chapter 4 identifies intrinsic motivational factors and examines non-economic policy tools to promote agroforestry implementation based on these intrinsic drivers. A structural equation model demonstrates that in line with the Theory of Planned Behaviour individual attitude, subjective norm, and perceived behavioural control influence farmers' intentions to adopt agroforestry systems with diverse tree species. Based on these results, this chapter tests three policy interventions, which target farmers' attitude, subjective norm, and perceived behavioural control respectively. The simulations show that farmers' intention to implement the sustainable system is most strongly increased by an information campaign that promotes agroforestry benefits and thereby positively impacts small-scale farmers' attitudes. Disseminating information regarding social norms to reinforce perceptions of subjective norms also increases farmers' intention to implement agroforestry systems. Another successful policy option is training provision to improve perceived behavioural control. Despite the positive effects of the three interventions, their impact on the small-scale farmers' intentions is rather low. To maximize the interventions' effectiveness, they should be implemented simultaneously. Overall, the results show that intrinsic motivation plays an important role for adoption decisions. Consequently, policy instruments addressing intrinsic drivers have potential to strengthen adoption intentions and, therefore, provide an alternative to financial incentives.

Chapter 5 focusses on the consequences of agroforestry adoption for humans and the environment. According to the simulations, farmers are willing to implement agroforestry. Thereby, they increase and diversify their incomes compared to a scenario without agroforestry, as the simulations show. Environmental benefits due to agroforestry adoption include higher carbon sequestration due to increased tree biomass and improved biodiversity. These positive effects even intensify over time. The simulation scenario with increasing temperature suggests that agroforest expansion presents a coping strategy towards climate change for small-scale farmers. Although climate change negatively affects biodiversity in both scenarios, the simulation results indicate significantly higher biodiversity levels if farmers implement agroforestry compared with the traditional agricultural systems. Overall, the fourth essay highlights the multiple benefits of agroforestry adoption for small-scale farmers and their environment over time, especially under climate change.

Keywords: Agricultural Innovations; Agroforestry; Innovation Adoption; Decision-making; Agent-based Modelling

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List of Abbreviations

ABM	Agent-based model
ANOVA	Analysis of Variance
BASAR	Biodiversity and Adoption of Small-scale Agroforestry in Rwanda
BLE	Federal Office for Agriculture and Food
BMEL	Federal Ministry of Food and Agriculture
BMU	Federal Ministry for the Environment, Nature Conservation, and Nuclear Safety
C	Celsius
CIFOR	Center for International Forestry Research
cm	Centimetre
CO_2	Carbon dioxide
DF	Degrees of Freedom
e.g.	exempli gratia
FAO	Food and Agriculture Organization of the United Nations
FoSeZa	Food Security in Rural Zambia
ICRAF	World Agroforestry
IKI	International Climate Initiative
IPCC	The Intergovernmental Panel on Climate Change
Kcal	Kilocalorie
Kg	Kilogram
Km	Kilometre
m	Metre
Mio	Million
mm	Millimetre
NGO	Non-Governmental Organization
NISR	National Institute of Statistics of Rwanda
ODD	Overview, Design concepts, Details
ODD + D	Overview, Design concepts, Details + Decision-making
ODK	Open Data Kit
p.p.	Percentage points

PBC	Perceived Behavioural Control
PLS-SEM	Partial Least Squares Structural Equation Model
RPG	Role-Playing Game
RWF	Rwandan Franc
SD	Standard deviation
SES	Social-ecological system
SN	Subjective Norm
TPB	Theory of Planned Behaviour
UN	United Nations
UNEP	United Nations Environment Programme
US	United States
WBGU	German Advisory Council on Global Change

1. Introduction

1.1 Motivation

Achieving global food security is one of the central challenges in the Anthropocene (FAO et al., 2021; Fraser et al., 2016). As economies grow and natural resources degrade, agricultural systems experience more pressure to produce sufficient food for the world's rising population (Calicioglu et al., 2019; Piñeiro et al., 2020). Additionally, inappropriate land management endangers land productivity and biodiversity conservation (FAO, 2018; Hilbrand et al., 2017). Climate change is another major factor threatening agriculture (Anderson et al., 2020; IPCC, 2019; World Bank, 2020). The negative consequences of climate change are likely to adversely affect various regions with most severe consequences expected in developing countries (Bathiany et al., 2018; FAO, 2016). Small-scale farmers in these countries are particularly vulnerable due to their high dependence on agriculture for livelihoods and income (FAO, 2016). Moreover, in Asia and Africa, where the prevalence of undernourishment is already severe, climate change is projected to further aggravate food insecurity (FAO et al., 2021). Addressing these challenges requires a transformation towards sustainable agriculture (FAO, 2016; Piñeiro et al., 2020; Reed et al., 2017).

Sustainable agricultural practices are frequently promoted as promising pathways to advance this agricultural transition because they can contribute to fight poverty and food insecurity, increase productivity, and mitigate climate change simultaneously (Piñeiro et al., 2020; WBGU, 2021). One of these sustainable agricultural practices is agroforestry, a land use system in which trees are managed along with crops and/or livestock (FAO, 2013). Integrating trees into agricultural landscapes provides multiple benefits: it generates food and non-food products, regulates nutrient and hydrological cycling, prevents soil runoff, and sequesters carbon among others (Kuyah et al., 2016; Wangpakapattanawong et al., 2017). Moreover, agroforestry systems can support biodiversity conservation, especially if they include diverse tree species (Santos et al., 2019). Small-scale farmers from developing countries can benefit from trees on farms in particular due to improved resilience and adaptive capacities (UNEP, 2011; Wangpakapattanawong et al., 2017). Thus, agroforestry offers high potential to address the multiple challenges faced by the agricultural sector (Mukuralinda et al., 2016; Noordwijk et al., 2011).

However, despite their various advantages, agricultural practices such as agroforestry remain underutilized by small-scale farmers in many regions, especially in Sub-Saharan Africa and also in some parts of Asia (Dhyani et al., 2021; Do et al., 2020; Macours, 2019). Increasing farmers' uptake of these practices on the pathway towards sustainable agriculture requires effective policy support (FAO, 2016; Kanter et al., 2016; Piñeiro et al., 2020). To develop effective interventions, policy-makers need to be able to assess the impact of their instruments and, thus, understand what drives farmers' adoption decisions (Groeneveld et al., 2017; Malawska et al., 2014; Meijer et al., 2015; World Bank, 2015). Yet, it remains a challenge to connect the top-down concepts of national policy instruments and global negotiations aimed at advancing the agricultural transformation with the bottom-up processes of how farmers make land use decisions (Noordwijk, 2020).

To connect farmers' land use decisions with emerging consequences under different policy scenarios, agent-based modelling offers a promising tool (Ahrweiler, 2017; Gilbert et al., 2018; Huber et al., 2018). An agent-based model (ABM) provides a computational method that represents a social-ecological system (SES) as a collection of autonomous entities named agents (Abdou et al., 2012; Bonabeau, 2002). Thereby, ABMs are able to represent agents' heterogeneous attributes, objectives, and behavioural rules (Smajgl et al., 2011; Smajgl and Bohensky, 2013; Wilensky and Rand, 2015). As a bottom-up approach, ABMs can simulate human-human and human-environmental interactions on the micro-level as well as system-level outcomes emerging from these interrelations (An, 2012; Rounsevell et al., 2012; Smajgl et al., 2011). Capturing such dynamic feedbacks is important in the context of agricultural adoption processes because farmers' decisions, their land use, and behaviour of other farmers can impact each other, while farm-level decisions influence the resulting land cover in the landscape (Bonabeau, 2002; Matthews et al., 2007; Verburg, 2006). Moreover, ABMs can explicitly represent human decision-making. Therefore, they can shed light onto the decision-making process itself and the underlying drivers such as motivations and preferences (An, 2012; Kiesling et al., 2012; Smajgl et al., 2011; Smajgl and Bohensky, 2013; Villamor et al., 2012). By conducting experiments in a virtual setting, this methodology is well-suited for investigating how farmers react to alternative policy interventions (Klabunde and Willekens, 2016; Silverman et al., 2011). Thus, ABMs can provide a valuable complement to econometric approaches (Huber et al., 2018; Kiesling et al., 2012), which many authors implement for analysing agricultural adoption decisions (e.g. Ashraf et al., 2015; Beyene et al., 2019; Gebru et al., 2019; Jara-Rojas et al., 2020; Sabastian et al., 2019).

Given the need for a sustainable agricultural transformation, this thesis implements agent-based modelling and simulations to support policy-makers in designing and implementing effective interventions that increase farmers' uptake of innovative sustainable practices in rural Asia and Africa. Hence, innovation diffusion processes and the underlying adoption decisions take a central role. This thesis includes four essays, each addressing different phases of the innovation-decision process. Specifically, the thesis uses agent-based modelling and simulations to 1) optimize knowledge diffusion in farming communities, 2) explain farmers' innovation adoption decisions, 3) identify intrinsic adoption drivers and assess how effectively non-economic policy interventions targeting these drivers improve adoption intentions and 4) investigate how agroforestry adoption influences humans and the environment over time.

The subsequent section presents the conceptual framework of the thesis. Section 1.3 introduces the essays' research topics and objectives, followed by section 1.4, which presents the datasets. Section 1.5 summarizes the essays' results and conclusions. Section 1.6 presents the outline of the overall thesis and highlights the author's contributions to each chapter. The subsequent chapters 2 to 5 contain the individual essays.

1.2 Conceptual Framework for Analysing Farmers' Adoption Decision Process across Different Stages

To study adoption behaviour of novel practices, Rogers (2003) proposed a model describing the innovation-decision process. The author defined innovation as "an idea, practice, or object that is perceived as new by an individual or other unit of adoption" (Rogers, 2003, p. 12). According to his framework, the first stage in the innovation-decision process is knowledge, which occurs when an individual (or other decision-making unit) discovers the innovation's existence and learns how it functions. Second, persuasion takes place when the individual generates a positive or negative attitude towards the innovation. The decision is made when the individual undertakes actions that result in a choice to implement or reject the innovation during the third stage. Fourth, once the individual puts a new idea into practice, implementation occurs. Confirmation takes place in the fifth stage when the individual reinforces a decision already made or reverses this earlier choice if exposed to conflicting signals about the innovation (Rogers 2003). Accordingly, decision-making comprises different steps and results in a certain behaviour as the outcome of this process (Schlüter et al., 2017). In the case of agricultural innovations, adoption affects not only the farmer as the decision-making unit itself, but can also influence other individuals and the environment (Matthews et al., 2007; Verburg, 2006). Thus, a last stage referring to the consequences was added to the innovation-decision process, as figure 1.1 illustrates. This thesis analyses farmers' adoption decisions across these stages, and the four essays provide insights into the knowledge, persuasion, decision, and consequences stage.

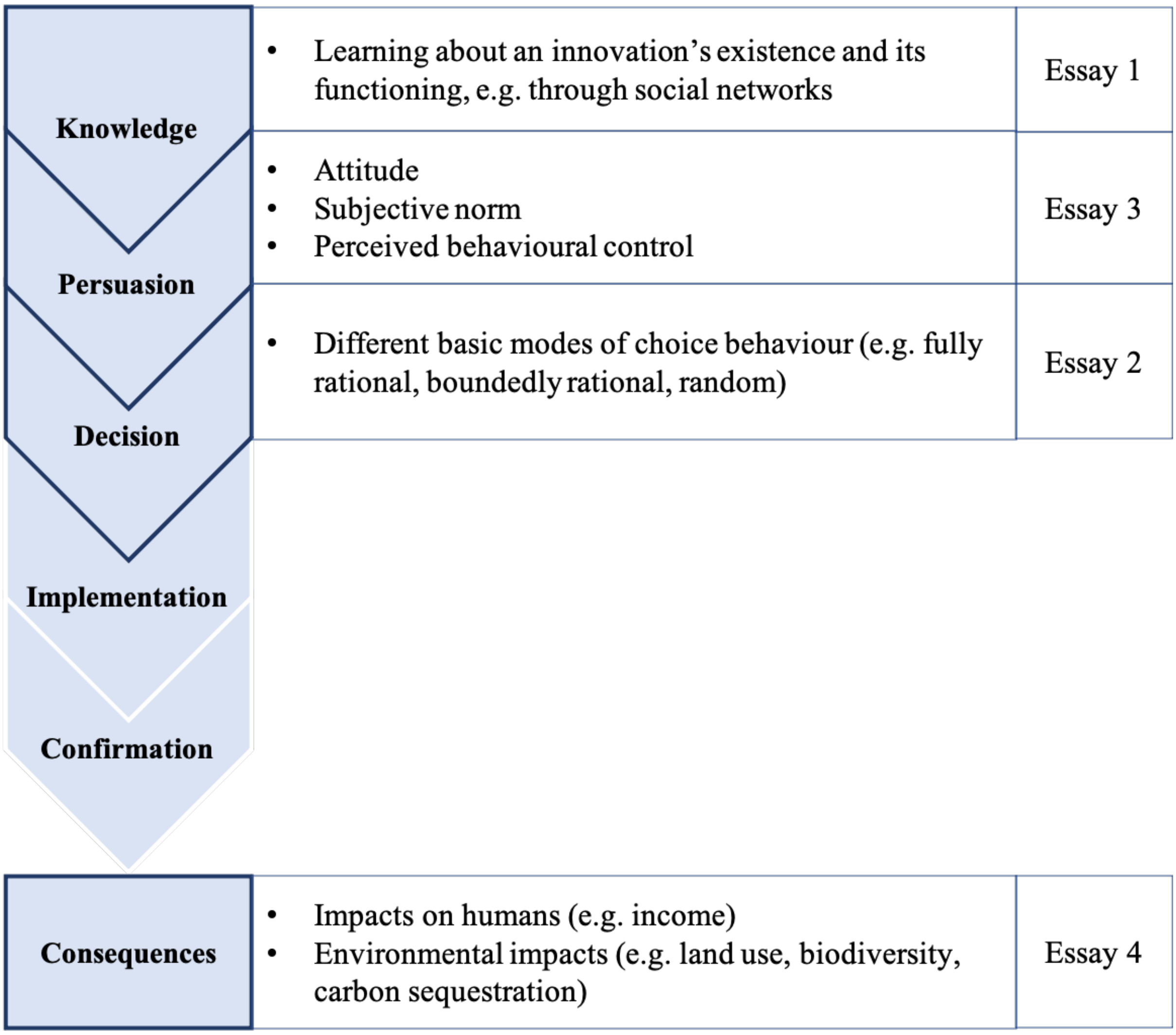

Figure 1.1: *Stages in the innovation-decision process*

Source: adapted from Rogers (2003).

1.3 Research Topics and Contribution of the Essays

The first essay, which focuses on the knowledge stage of the innovation-decision process, is based on the premise that farmers exchange information with their social contacts (Feder et al., 1985; Matuschke, 2008). Hence, policy-makers can use social networks to disseminate knowledge, e.g. on agricultural innovations, within a community. Thereby, policy-makers select a subset of farmers who receive the information from the official agency. They then rely on these 'seeds', the initially informed farmers, to spread the knowledge with their social contacts. Since all other farmers depend on the seeds to receive the information, seed selection is critical for successful knowledge dissemination (D'Angelo et al., 2017; Genius et al., 2014; Magnan et al., 2015). The first essay compares different seed selection strategies to optimise information diffusion within a sparse social network. Specifically, an agent-based model, which is applied to a case study in rural Zambia, opposes randomly selected seeds with seed selection criteria related to the farmers' position in the network (centrality criteria) and hierarchy. The essay aims to answer the following research questions:

1. What is the optimal seed selection criterion among random choice, hierarchy (village heads), degree centrality, betweenness centrality, closeness centrality, and eigenvector centrality for improved information diffusion?
2. What is the optimal seed number for improved information diffusion?
3. How does the effectiveness of the seed selection criterion depend on the seed number?

Although many studies examine innovation diffusion and acknowledge information as an essential prerequisite for adoption, research addressing the improvement of information spread through social networks remains limited. Thus, this essay adds to the scarce research by investigating the potential of adequate seed selection strategies for successfully disseminating agricultural knowledge. It expands previous research as it includes the criterion of hierarchy, which can have high practical relevance in developing countries. Moreover, the study considers both the seed selection criterion and the seed number. Using data from a rural case study region located in a developing country, where farmers rely on their social networks as an information source, the analysis complements theoretical approaches and evidence from high income countries.

The second essay addresses the issue of low innovation adoption rates among small-scale farmers in developing countries (Do et al., 2020; Macours, 2019). To be able to provide efficient interventions that raise low adoption rates, policy-makers need to understand what motivates farmers' adoption decisions (Groeneveld et al., 2017; Malawska et al., 2014; World Bank, 2015). The second essay compares different commonly applied behavioural approaches to explain small-scale farmers' adoption decisions. Particularly, it evaluates the following approaches: random decision-making, discounted and non-discounted profit maximization (theories of perfect rationality), satisficing as well as fast and frugal decision tree heuristics (bounded rational theories), the Theory of Planned Behaviour (TPB) (psychological theory), and an econometric approach. Thereby, the second essay focusses primarily on the decision stage of the innovation-decision process. The various behavioural approaches are applied to the decision to adopt a novel agroforestry system. An agent-based simulation model is developed using data from a study region in rural Rwanda. It predicts agroforestry adoption rates based on the different behavioural approaches. To identify the approach with the highest explanatory potential, the results are compared with adoption rates observed in a role-playing game (RPG), which was conducted for validation. The second essay's research questions are as follows:

1. How does the selection of a behavioural approach to explain farmers' decision-making affect predicted adoption rates?
2. Which behavioural approach has the highest validity compared with adoption rates observed in the RPG?

The contribution of this essay is twofold. First, the analysis of several relevant behavioural theories including the TPB and an econometric approach extents previous comparisons of behavioural approaches which mainly focus on optimization and deviations from perfect rationality to investigate farmers' decision-making. Second, previous comparisons are inconclusive as to which approach has the highest explanatory power. Hence, validating the behavioural approaches using a RPG contributes to identifying a well-suited approach to explain agroforestry adoption behaviour. Thereby, the essay adds to a basis for future research that relies on understanding, representing, and forecasting farmers' adoption decisions.

The third essay focuses on how farmers can be encouraged to adopt agroforestry. Many authors conclude that income is an important motivational factor for agricultural decisions (e.g. Cole, 2010; Iiyama et al., 2018; Oduro et al., 2018; Staton et al., 2022). However, behavioural evidence suggests that besides financial considerations adoption decisions are also influenced by intrinsic drivers (Bagstad et al., 2020; Dessart et al., 2019; Jha et al., 2021; Meijer et al., 2015). This essay identifies relevant intrinsic drivers of farmers' intentions to adopt agroforestry systems with diverse tree species based on the TPB. This theory proposes that behaviour results from a deliberate decision process and that behavioural intentions are formed by attitude, subjective norm (SN), and perceived behavioural control (PBC) (Ajzen, 1991). To assess the potential of alternative incentives addressing these intrinsic drivers, the essay tests non-economic interventions derived from the TPB for enhancing farmers' intention to adopt agroforestry with diverse tree species. An agent-based model simulates 1) an information campaign to spread awareness of agroforestry benefits to strengthen positive attitudes, 2) a policy intervention informing farmers about social norms to reinforce their perceived SN, and 3) a strategy focussing on trainings to improve farmers' PBC over planting diverse tree species on their farms. Therefore, this essay relates mainly to the persuasion stage. A modified version of the agent-based model developed for the second essay is applied to the same case study area in rural Rwanda. The essay aims to answer the following research questions:

1) What are the intrinsic drivers of farmers' intention to adopt agroforestry with diverse tree species?
2) How effectively can non-economic interventions targeting farmers' intrinsic motivation enhance their intention to adopt agroforestry?

The chapter addresses the need for more research investigating how effectively non-economic policy instruments can facilitate behavioural change among small-scale farmers (Lourenco et al., 2016; Palm-Forster et al., 2019; Rose et al., 2018). Adding to the limited evidence of behaviourally-informed interventions in the field of agriculture, the essay provides novel insights into the effectiveness of measures that target attitudes, SN, and PBC to encourage agroforestry adoption. By assessing the potential of non-economic, cost-effective strategies that promote agroforestry, it provides insights for policy development.

The fourth essay also investigates small-scale farmers' adoption of agroforestry as a sustainable agricultural practice, but the main focus shifts to the consequences stage. Although many authors have studied agroforestry adoption in low-income countries and its associated determinants or biophysical processes, evidence on the social-ecological benefits of trees on farms is still limited (Miller et al., 2019; Reed et al., 2017). However, knowledge about agroforestry's contribution to sustainability objectives is important to ensure that this practice is not overlooked in relevant policy processes (Miller et al., 2017). To develop appropriate interventions, policy-makers should adequately assess the consequences of agroforestry implementation and, therefore, consider the interlinked dynamics between farmers' decisions, land use, and further ecosystem processes (Müller-Hansen et al., 2017; Rounsevell et al., 2013). The fourth essay investigates the interrelated human-environmental aspects of agroforestry adoption on the household and landscape level. Additionally, it assesses the potential of agroforestry to contribute to the sustainable agricultural transformation in the long-term. It investigates small-scale farming households' decision to adopt a novel biodiversity-enhancing agroforestry system and the consequences for incomes, biodiversity, and carbon sequestration. An agent-based simulation model is calibrated to an Indonesian case study. It compares a scenario with traditional agricultural practices to a scenario with the option to implement an innovative agroforestry system. Additional to the baseline scenario with constant temperatures, the model introduces a climate change scenario with a temperature rise of 1.5°C. The fourth essay investigates the following research questions:

1. How do farmers' decisions to adopt agroforestry impact their livelihoods compared to a scenario without agroforestry?
2. How do farmers' decisions to adopt agroforestry impact biodiversity levels and carbon sequestration compared to a scenario without agroforestry?
3. How do these results change in a climate change scenario with a 1.5°C temperature rise?

This essay links household-level, farm-level, and emerging dynamics related to agroforestry adoption and provides insights into the consequences for livelihoods and the environment. Thereby, it complements existing econometric and biophysical studies. Simultaneously, the ABM addresses the need for studies considering human-environmental aspects over time to assess the potential of agroforestry to contribute to the sustainable agricultural transformation in the long-term. Additionally, the scenario with rising temperatures investigates how agroforestry can function as a measure for climate change mitigation and adaptation.

Overall, this thesis contributes to an enhanced understanding of farmers' innovation adoption behaviour as a multi-step decision-process. The essays provide insights into the internal stages that precede adoption behaviour as well as the decisions' consequences. Thereby, they highlight potential entry points for policy interventions along this process.

1.4 Data

The data for the first essay originates from the project "Food Security in Rural Zambia" (FoSeZa), funded by the German Federal Ministry of Food and Agriculture (BMEL). The research was applied to a case study in the Mantapala region, which is located within the Congo Basin in northern Luapula Province of Zambia. This region was chosen as a study site because of its features such as subsistence farming, high levels of malnutrition, remote location, and lack of infrastructure development. In April 2018, a structured survey was conducted as part of a village census. It covered a total of 264 households. The questionnaire consisted of information about sociodemographic characteristics, agricultural activities, expenditures, and natural resource use among others. Furthermore, it included a detailed section on social capital and information exchange. Complementing the survey, Global Positioning System data were collected to record the households' locations.

For the second and third essay, data were collected in the context of the project "Harnessing the potential of trees on farms for meeting national and global biodiversity targets" funded by the Federal Ministry for the Environment, Nature Conservation, and Nuclear Safety (BMU). The dataset originates from a case study located in Western province of Rwanda, where three sectors (Karago, Jenda, and Nyundo) were selected for the research. These sectors represent the farming culture in highlands of rural and densely populated countries, where farmers have small plots on sloping land and face high environmental risks including soil erosion, landslides, and flooding. From this area, a total of 145 small-scale farmers were randomly selected to participate in a structured survey. The interviews took place in fall 2020 and covered a total sample of 145 small-scale farmers. The survey contained questions on the households' socio-demographics and agricultural activities among others. It also comprised a section on the TPB to assess farmers' attitude, SN, PBC, and intention to cultivate agroforestry systems on their land. From the survey respondents, 72 farmers were randomly selected to participate in a RPG. The RPG was used to validate the ABM developed for the second essay. The ABM build for the third essay extends and modifies the model used in the second essay.

The fourth essay changes the location from Africa to Asia. The data used for the fourth essay's ABM also originates from the project "Harnessing the potential of trees on farms for meeting national and global biodiversity targets" funded by the BMU. The developed ABM is applied to an Indonesian case study in Kapuas Hulu regency, Borneo. Within Kapuas Hulu, Batang Lupar district was chosen as a study site because the local landscape is still traditionally managed and the study area is located in a buffer zone between two national parks with direct impacts on the Danau Sentarum National Park wetlands. From this district, 139 households from different settlements were randomly selected to participate in a survey. The structured interviews were conducted between May and September 2014. The questionnaire included segments on demographics, agricultural activities, use of natural resources, food security, and social networks among others. Remote sensing data from the year 2014 and data describing the landscape, which were collected via an unmanned aerial vehicle for the years 2016 and 2017, complemented the survey as input for the ABM. Additionally, the model used ecological indicators to estimate biodiversity levels and carbon sequestration including tree species richness, tree density, basal area, and bird richness among others.

1.5 Results and Conclusions

The first essay, which analyses how seed selection influences knowledge diffusion within a social network in Zambia, shows a significant impact of the seeding strategy on information spread. Informing farmers with the highest degree centrality, who have the most social connections and strongest direct influence (Barbuto et al., 2019; Delre et al., 2010), leads to quickest and most widespread knowledge diffusion. Also selecting village heads as seeds results in relatively widespread diffusion. Furthermore, farmers with high betweenness centrality appear promising as seeds. Because these farmers connect different network parts, they are especially well-suited as seeds in the case study's sparse network. In contrast, the diffusion success of both closeness and eigenvector centrality as seed selection criteria is limited, especially in the short run, as these indicators put comparatively little weight on immediate connections (Borgatti et al., 2018; Chen et al., 2017; Muller and Peres, 2019). The simulation results show that a higher seed number significantly increases diffusion reach, but the marginal effects of additional seeds decline. The scenario varying both seed selection criterion and seed set size reveals that also the interaction thereof significantly influences diffusion reach and speed. Overall, these insights can support policy-makers and extension officers with constrained resources to optimize information spread through social networks in rural areas in developing countries. The findings demonstrate that a cost-efficient way for providing knowledge to a farming community is to initially inform farmers with high degree or betweenness centrality. Informing village heads also poses a promising alternative to spread information in rural areas in developing countries, but possible side effects related to hierarchy should be considered. Policy-makers can improve information dissemination if they increase the number of seeds, but the seed set number influences the performance of certain seeding strategies. Hence, policy-makers should carefully consider the number of seeds in addition to the seed selection criterion to successfully provide farmers with agricultural information.

Focussing on the adoption decision itself, the second essays' simulations demonstrate that the selection of a behavioural approach to explain Rwandan farmers' decisions significantly impacts predicted agroforestry implementation rates. Observations from the RPG as a validation tool were most similar to adoption rates predicted based on the TPB, which therefore shows the highest validity compared to the theories of bounded and perfect rationality, the econometric approach, and random-decision-making. The TPB emphasizes the key role of intrinsic drivers such as environmental considerations besides financial motivations. Similar to the TPB, the econometric approach also delivers forecasts close to those from the RPG. This indicates the potential of using econometric approaches for predicting adoption rates. However, insights regarding the causal relationships of the decision-making process derived from regression analysis are limited (An, 2012; Kiesling et al., 2012; Villamor et al., 2012). Both rational choice approaches overpredict adoption rates. Their low validity is in line with the literature that criticizes this theory due to its unrealistic assumptions (Gigerenzer and Goldstein, 2011, 1996; Simon, 1972). Both bounded rationality concepts underestimate implementation. This implies that heuristics as non-optimizing behaviour and limited knowledge restrict adoption. Because the analysed approaches are based on distinct premises and capture specific features of the decision-making process, they also differ with respect to the derived policy recommendations. The bounded and perfect rationality theories and also the TPB indicate that financial incentives, input provision, and trainings promote on-farm tree planting as they address possible obstacles in the adoption process. Moreover, the TPB and econometric approach highlight intrinsic motivation as a vital driver for adoption. Hence, strengthening intrinsic motivations seems promising to raise low agroforestry adoption rates. Overall, the second essay's findings underpin the importance of choosing a well-suited behavioural approach and to account for non-economic drivers when studying adoption behaviour.

Concentrating on the persuasion stage, the third essay identifies intrinsic motivational factors based on the TPB and tests non-economic policy interventions targeting these drivers to improve agroforestry adoption intentions among Rwandan farmers. In line with the TPB, the results demonstrate that socio-cognitive aspects including farmers' attitude, SN, and PBC are vital to their adoption decision. Consequently, interventions targeting these intrinsic divers significantly impact farmers' intention to adopt agroforestry systems with diverse tree species, as the simulations demonstrate. Among the interventions, the information campaign that targets attitude and educates farmers about agroforestry benefits is most effective. Farmers' intention improves significantly also if policy-makers reinforce normative beliefs by informing them about social norms held by the farmers' family and friends. If farmers participate in trainings that increase their confidence and, thus, perceived control over cultivating diverse tree species, intention improves significantly as well. However, the effectiveness of each intervention is relatively small because the farmers already hold positive attitudes, strongly perceive SN, and are confident about their PBC even without any intervention. Implementing the interventions simultaneously enhances the policy impact of the individual options, especially when the information campaign directed at attitude is combined with an intervention targeting SN or PBC. Thus, the results provide specific recommendations for policy design. The findings highlight that policy-makers should account for intrinsic drivers when developing interventions. They should implement interventions that target attitude, SN, and PBC as alternatives to financial incentives. To increase the impact on adoption rates, policy-makers should implement the interventions in combination.

Analysing the consequences of successful agroforestry adoption in Indonesia, the fourth essay demonstrates that agroforestry offers multiple benefits for farmers and the environment. The simulations show that farmers decide to adopt agroforestry and thereby diversify their livelihoods. Due to a change in labour allocation, farmers harvest less rice from traditional shifting cultivation, but their cash income greatly increases compared to the scenario without agroforestry. This points to the potential of agroforestry to alleviate poverty. The farmers expand the area under agroforestry at the cost of land cultivated with jungle rubber or rice, while the amount of natural forest remains constant. Agroforestry adoption and the related land use changes significantly improve biodiversity conservation and carbon sequestration, with a positive trend over the years. The climate change scenario demonstrates that agroforestry appears even more promising under a simulated rise in temperature of 1.5°C: as a reaction to reduced rice yields, farmers increasingly adopt the agroforestry system and raise their cash income. These findings indicate the potential of this practice as a coping strategy towards climate change for small-scale farmers. Although climate change negatively affects biodiversity in both scenarios, the simulations predict significantly higher biodiversity levels if farmers implement agroforestry. The amount of carbon sequestered even remains constant in the agroforestry scenario despite rising temperatures. In general, the simulation findings indicate that agroforestry creates multiple benefits for small-scale farming households and the environment in the short- as well as long-term, especially if temperatures rise. Therefore, policy-makers should promote agroforestry practices as a way to alleviate poverty, fight food insecurity, and mitigate climate change. Thereby, they could raise awareness of the diverse economic and environmental benefits in the short- as well as long-term to stimulate demand. Furthermore, policy-makers should remove possible adoption barriers through input provision and trainings. Alternatively, they could financially compensate this environmentally friendly practice providing several ecosystem services.

1.6 Outline

Table 1.1 provides an overview of the essays contained in this thesis.

Table 1.1: *Thesis overview.*

Essay	Title	Authors	Status
1	Seed Selection Strategies for Information Diffusion in Social Networks: An Agent-Based Model Applied to Rural Zambia	Beatrice Nöldeke, Etti Winter, Ulrike Grote	Published in: *Journal of Artificial Societies and Social Simulation* 2020, 23, 1–24. Earlier version presented at: *International Conference on Economic Modeling and Data Science*, July 2019
2	Explaining Agroforestry Adoption in Rural Rwanda: an Agent-based Simulation Study of Human Decision-making	Beatrice Nöldeke, Etti Winter, Elisée Bahati Ntawuhiganayo	Resubmitted after first review: *Ecological Economics* Earlier version presented at: *Social Simulation Conference*, September 2021
	Survey Data for Analysing Farmers' Intention to Adopt Agroforestry in Rural Rwanda: a Partial Least Squares Structural Equation Modelling (PLS-SEM) Approach	Beatrice Nöldeke, Ronja Seegers, Etti Winter, Elisée Bahati Ntawuhiganayo	Parts of the Appendix are submitted to: *Data in Brief*
3	Promoting Agroforestry in Rwanda: the Effects of Policy Interventions Derived from the Theory of Planned Behaviour	Beatrice Nöldeke	Published in: *Hannover Economic Papers* 2022, no. 693. Submitted to: *Sustainable Production and Consumption* Accepted for: *Global Conference on Economic Geography*, June 2022
4	Simulating Agroforestry Adoption in Rural Indonesia: The Potential of Trees on Farms for Livelihoods and Environment	Beatrice Nöldeke, Etti Winter, Yves Laumonier, Trifosa Simamora	Published in: *Land* 2021, 10.

The author contributed to the chapters as follows: for the first essay, the author was involved in the survey design, the data collection in Zambia, and the cleaning. Ulrike Grote and the author jointly conceptualized this essay. The author developed the agent-based model, analysed the results, wrote, and (re-)submitted the essay with contributions from Ulrike Grote and Etti Winter. The second essay and the respective ABM were conceptualized and developed by the author with contributions from Etti Winter. The author contributed to designing the questionnaire and supervising the data collection, which Elisée Bahati Ntawuhiganayo conducted on site. The author cleaned and processed the data. The author analysed the results, wrote, and (re)submitted the essay with contributions from Etti Winter and Elisée Bahati Ntawuhiganayo. Additional to the main essay, parts of the supplementary material describing the survey data and selected results were submitted separately. The author conceptualized this part jointly with Ronja Seegers and wrote it with contributions from all co-authors. The author was solely responsible for the third essay. The fourth essay was jointly conceptualized by the author, Etti Winter, and Yves Laumonier. Yves Laumonier and Trifosa Simamora provided data used as input for the ABM. The author developed the model, analysed the data, and wrote the essay with contributions from all co-authors.

Further work in progress includes a policy brief describing options to support agroforestry adoption in line with farmers' preferences. The author wrote the draft jointly with Ronja Seegers. Additionally, the author contributed to a collaboration with several co-authors with the working title "Is nudging founded in lazy problem analysis? Keeping your proposition attractive and removing barriers - improving outcomes of agricultural research for development projects". For this essay, the author was responsible for the literature review and wrote parts of the results and discussion. The author further contributed to rewriting the essay.

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3. Explaining Agroforestry Adoption in Rural Rwanda: an Agent-based Simulation Study of Human Decision-making

This chapter is submitted to:

Ecological Economics

Abstract

Small-scale farmers' adoption of sustainable agricultural practices such as agroforestry remains low in many regions, especially in Sub-Saharan Africa. Designing and implementing appropriate interventions to promote adoption requires an understanding of farmers' decision-making. Various approaches exist to explain human decision-making and the resulting behaviour. This study compares selected commonly applied behavioural approaches and provides insights into how well they explain farmers' decisions to adopt agroforestry. Based on socio-economic survey data from 145 rural Rwandan farming households, an agent-based simulation model is developed that simulates farmers' decision to implement diversified agroforestry systems. The model is validated against data from a role-playing game. The simulations confirm that the assumed behavioural approach to explain decision-making significantly affects predicted adoption rates. The Theory of Planned Behaviour exhibits the highest validity, followed by the econometric approach. Rational choice theory overestimates implementation, and bounded-rationality underestimates the share of adopters compared with the role-playing game. These findings indicate that, additional to financial drivers, intrinsic motivations such as climate change mitigation and environmental protection impact agroforestry adoption. Therefore, policy-makers should promote positive attitudes and educate about the benefits of agroforestry in addition to financial incentives to increase its implementation.

Keywords: Decision-making; Agent-based Modelling; Agroforestry Adoption; Theory of Planned Behaviour; Rational Choice Theory; Bounded Rationality; Small-scale Farming; Rwanda

3.1. Introduction

Factors such as climate change, degradation of natural resources, growing populations, and subsequently increasing demand for food hinder agricultural production systems to ensure global food security (FAO, 2018; Piñeiro et al., 2020). Moreover, inappropriate land management impedes land productivity, biodiversity conservation, and provision of further ecosystem services (FAO, 2018; Hilbrand et al., 2017). To combat these challenges, good stewardship of natural resources gains importance (Piñeiro et al., 2020; WBGU, 2021). In this context, sustainable agricultural practices have been increasingly promoted as a pathway to sustainably increase agricultural productivity, enhance adaptive capacities, and mitigate climate change (FAO, 2021; WBGU, 2021). One sustainable agricultural practice with high potential to address the mentioned challenges is agroforestry, the integration of trees into agricultural landscapes (Mukuralinda et al., 2016). By producing food, regulating nutrient and hydrological cycles, controlling soil erosion, and sequestering carbon, agroforestry provides several ecosystem services simultaneously, protects livelihoods, realizes environmental benefits, and contributes to climate change adaptation (Kuyah et al., 2016; Wangpakapattanawong et al., 2017). Especially small-scale farmers from developing countries can benefit from cultivating trees on farms since they are particularly vulnerable to climate change due to their high dependence on agriculture for livelihoods and income (FAO 2016). Despite the various benefits, adoption by small-scale farmers remains low in some regions, especially in parts of Sub-Saharan Africa (Do et al., 2020; Macours, 2019). Increasing low adoption rates of sustainable agricultural practices requires adequate support in the form of policy interventions (FAO, 2013; van Noordwijk et al., 2018). To tailor effective policy interventions that are attractive to farmers, policy-makers need to be able to assess the impact of policies and, therefore, understand farmers' preferences and what motivates their decisions to adopt (Groeneveld et al., 2017; Malawska et al., 2014; Meijer et al., 2015a; The World Bank, 2015).

Decision-making is a process that entails different steps as well as various basic modes of choice behaviour and results in a certain behaviour as the outcome of this process (Schlüter et al., 2017; Selten, 2001). Multiple theories and approaches have been developed to explain decision-making and the resulting behaviour (Schlüter et al., 2017). One well established economic model is based on the concept of full rationality and assumes that humans have perfect information and capacities to evaluate all alternatives without errors when maximizing their (expected) well-being (Sen, 1994; Simon, 1955, 2007; van Duinen et al., 2016). However, several authors point out limitations of rational choice theory because human rationality is bounded by restricted information availability, cognitive capacity, and environmental complexity (e.g. Green and Shapiro, 2014; Kahneman, 2003; Simon, 1990, 1959). In response to the limited explanatory power of rational choice theory, the concept of bounded rationality has been suggested and explored in recent decades (Gigerenzer and Goldstein, 1996; Gigerenzer and Selten, 2001a; Simon, 1990, 1972). Behavioural approaches taking bounded rationality into account include among others satisficing heuristics and fast and frugal decision tree heuristics (Gigerenzer and Goldstein, 1996; Gigerenzer and Selten, 2001b; Schilirò, 2018; Simon, 1972). Other approaches that address research on adoption include the Theory of Planned Behaviour, a psychological cognitive theory that links attitude, subjective norms (SN), perceived behavioural control (PBC), and intentions to behaviour (Ajzen, 1991; Scalco et al., 2017), and econometrics, which combine empirical data with statistical methods (e.g. Gebru et al., 2019; Sanou et al., 2019; Sood and Mitchell, 2009). The breadth of diverse behavioural frameworks raises the question of which approach is best suited to explain farmers' decision to adopt agroforestry.

For investigating different behavioural approaches to explain farmers' agricultural decisions, agent-based modelling and simulation can offer valuable methodologies (e.g. Brown et al., 2018; Janssen and Baggio, 2017; Richetin et al., 2009; Schindler, 2013; van Duinen et al., 2016). An agent-based model (ABM) provides a computational method that models a system as a collection of autonomous interacting entities named agents (Abdou et al., 2012; Bonabeau, 2002). Agent-based simulations refer to models in which the dynamic processes of agent interactions are simulated repeatedly over time (Macal and North, 2008). Agent-based modelling and simulation offer advantages for exploring social-ecological systems (SES) because they can explicitly represent individual decision-making and simulate dynamic feedbacks between humans, humans and their environment, as well as emerging phenomena on the system-level (An, 2012; Rounsevell et al., 2012; Smajgl et al., 2011). Capturing dynamic human-human and human-environmental interrelations is important in the context of agricultural adoptions because farmers' decisions, farm land use, and other farmers' behaviour influence each other, while farm-level decisions impact the emerging land cover in the landscape (Bonabeau, 2002; Matthews et al., 2007; Verburg, 2006).

Few authors compared alternative behavioural approaches to explain human decision-making in models of SES (Schulze et al., 2017). The results indicate that the behavioural underlying approach affects simulation outcomes and hence policy implications derived based on these approaches (Brown et al., 2018; Cabrera et al., 2010; Holtz and Nebel, 2014; Huber et al., 2018; Janssen and Baggio, 2017; Richetin et al., 2009; Schindler, 2013; Schreinemachers and Berger, 2006; van Duinen et al., 2016; Wens et al., 2020). The limited number of studies that investigate different behavioural approaches in SES focuses mainly on optimization and deviations from perfect rationality. Consequently, there remains a need for more studies regarding behavioural approaches to explain farmers' decision-making, for comparing alternative approaches, and for including the TPB in these comparisons (Caprioli et al., 2020; Huber et al., 2018; Reidsma et al., 2018; Schlüter et al., 2017; Schulze et al., 2017).

The purpose of this study is to compare selected commonly used behavioural approaches to explain farmers' decision to adopt diversified agroforestry systems. For this comparison, an agent-based simulation model simulates this decision based on the TPB as a psychological theory, non-discounted and discounted utility maximization as theories of perfect rationality, satisficing and fast and frugal heuristics as bounded rational theories, and an econometric approach to a scenario where farmers decide randomly. The developed model implements a series of simulations to predict farmers' adoption behaviour based on the different decision-making modules. To assess how well the approaches explain farmers' decision-making, the simulated adoption rates are compared with adoption rates observed in a role-playing game (RPG), which was conducted for validation.

The model is applied to a case study in rural Rwanda. The case study area is characterized by challenges including high pressure on the agricultural production systems, land degradation, and biodiversity loss (Bagstad et al., 2020; Iiyama et al., 2018; Mukuralinda et al., 2016). Thus, biodiversity-enhancing agroforestry offers a sustainable alternative to the traditional potato and wheat rotation system for mitigating and adapting to the challenges in the area.

This study aims to provide insights into the implications associated with the choice of a behavioural approach and the extent to which different behavioural approaches principally affect simulation outcomes, in our case smallholders' agroforestry adoption rates. This is important to improve the transparency of simulation models and their use for context-specific policy recommendations. Besides, the results may support modellers to decide which behavioural approach to implement for representing small-scale farmers' decision-making in this agricultural context. By providing insights into the approaches' suitability to explain farmers' decision to adopt diversified agroforestry in the case study area, the results contribute to a basis for further research that relies on explaining and predicting human behaviour in SES.

The article is structured as follows: section 3.2 describes the study area and data and introduces the agent-based simulation model. The next section presents the findings followed by a discussion of these results in section 3.4. Section 3.5 summarizes and concludes.

3.2 Data and Methodology

Study area

The research is applied to a case study in rural Rwanda. Rwanda is a small landlocked country located in Sub-Saharan Africa. Its topography is mountainous with altitudes ranging from 900 to 4500 m above sea level (Nduwamungu, 2011). Rwanda has a tropical climate with average annual temperatures of 18 °C. Annual rainfall averages 1111 mm (Mukuralinda et al., 2016). Rwanda is characterized by a high population density with 499 inhabitants per km2, making it one of the most densely populated countries (FAPDA, 2016; The World Bank, 2020). Around 38% of the Rwandan population live in poverty, and 16% in extreme poverty (National Institute of Statistics of Rwanda, 2018). The majority of the population depends on agriculture, and nearly 75% of the land area is used for farming (Mukuralinda et al., 2016). Due to Rwanda's dense and growing population, the agricultural sector is under high pressure to meet the increasing demand for food and energy, resulting in the ongoing conversion of forests into farmland (Bagstad et al., 2020; FAPDA, 2016; Iiyama et al., 2018). Combined with unsustainable land management, the agricultural expansion led to serious land degradation, soil erosion, declining soil fertility, and biodiversity loss (Bagstad et al., 2020; Mukuralinda et al., 2016). Soil erosion in Rwanda's hilly landscapes poses a particularly serious problem for agriculture (Karamage et al., 2016).

Because land scarcity and poverty restrict reforestation efforts and forests compete with food crop production systems, agroforestry is considered a powerful solution to the prevailing problems in the area (Nduwamungu, 2011). Although policy-makers, NGOs, and donors promote agroforestry through initiatives such as the Rwanda 2020 Vision, insufficient consideration of farmers' opinions on preferred tree species, niches, and density has impeded implementation (Mukuralinda et al., 2016). As a consequence, the degree of adoption varies across regions and is dominated by Eucalyptus, an exotic species (Mukuralinda et al., 2016). Policy-makers, NGOs, and donors therefore need to understand how farmers make decisions to implement biodiversity-enriching agroforestry practices in a sustainable manner.

Diversified agroforestry system

This study explores farmers' adoption of a diversified agroforestry system that combines Irish potatoes (*Solanum tuberosum L.)* and wheat (*Triticum aestivum L.*) rotations with *Grevillea robusta, Alnus acuminata* Kunth, and *Markhamia lutea* trees in a hedgerow system (Ministry of Environment – Rwanda, 2020). *Grevillea robusta*, a semi-deciduous tree providing timber and fuelwood, is commonly cultivated by Rwandan farmers as a share or boundary tree, windbreak, or for contour planting to control soil erosion because this multipurpose tree is highly adaptable and compatible with many crops (Bucagu et al., 2013; Ministry of Environment – Rwanda, 2020; Orwa et al., 2009). *Alnus acuminata*, also known as "Andean alder", is a fast-growing deciduous tree from the *Betulaceae* family, introduced to tropical Africa for timber production. Further ecosystem services offered by *Alnus acuminata* include soil improvement due to nitrogen fixation, soil erosion control, and provision of stakes among others (Bosch, 2009; Ministry of Environment – Rwanda, 2020). The *Markhamia lutea* or Nile tulip, from the family *Bignoniaceae*, also produces firewood. The evergreen tree, native to eastern Africa, further provides medicinal leaves, shade, poles, controls control, improves soil, and has aesthetical value (Ministry of Environment – Rwanda, 2020; Orwa et al., 2009).

Data collection

Within Rwanda, three sectors in Western province were chosen for the research (Karago, Jenda, and Nyundo) (figure 3.1). These sectors are representative of the farming culture in highlands of rural and densely populated countries where farmers have small-sized plots on sloping land with high environmental risks such as erosion, landslides (upstream), or floodings (downstream). From this area, a total of 145 small-scale farmers were randomly selected for structured survey interviews. The interviews took place in October to November 2020 and included questions regarding the households' socio-demographics, agricultural activities, attitudes, SN, PBC, and intentions towards diversified agroforestry. In addition, a role-playing game (RPG) was conducted with 72 farmers. Section 2.5.4 "Calibration, verification, and validation" provides further details regarding the RPG.

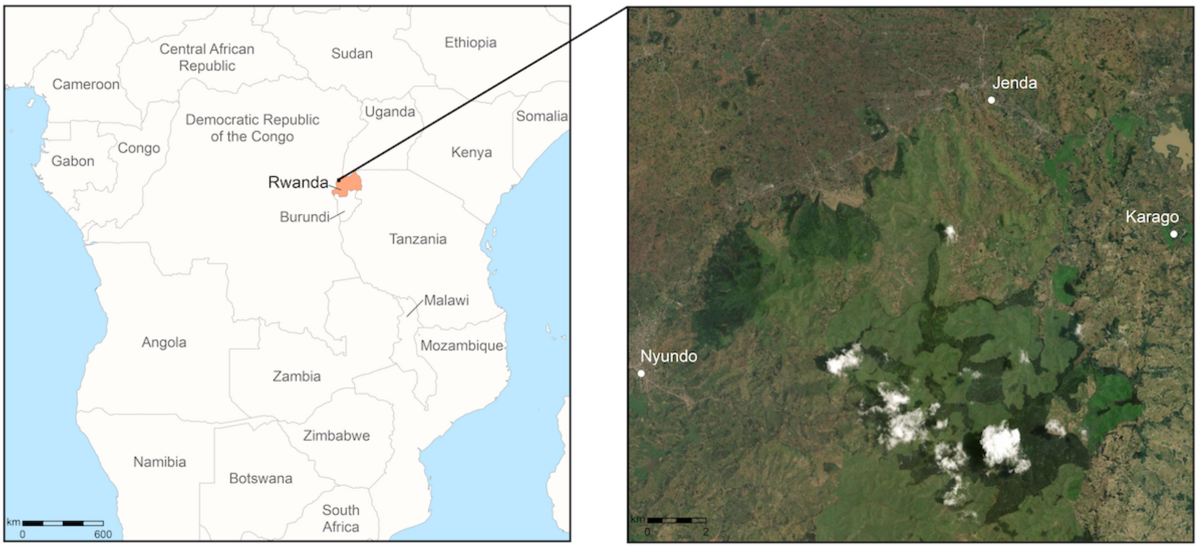

Figure 3.1: *Study area*

Data analysis

The data analysis comprised several components. First, a descriptive analysis of the survey data was performed in Stata 16 (StataCorp, 2019). Using the same software, a logit regression model was used to estimate the probabilities of farmers' adoption of diverse agroforestry systems. The TPB was assessed via a Partial Least Squares Structural Equation Model (PLS-SEM) using SmartPLS 3 (Ringle et al., 2015). A SEM is a multivariate statistical framework that can be used to investigate relationships between directly and indirectly observable (latent) variables (Stein et al., 2012). A PLS-SEM aims to maximize the proportion of explained variance of endogenous latent variables and allows behavioural predictions (Hair et al., 2017). Next, an agent-based simulation model, which is further described in the subsequent section, was developed and implemented. Lastly, the simulation results were analyzed by applying Analysis of Variance (ANOVA) to compare the different behavioural approaches in Stata 16. The Appendix C contains further information about data analysis and results.

Agent-based simulation model

The subsequent section describes the implemented agent-based simulation model following the Overview, Design Concepts and Details + Decision-making protocol (Grimm et al., 2020, 2010, 2006; Müller et al., 2013).

Overview

Purpose: The Biodiversity and Adoption of Small-scale Agroforestry in Rwanda (BASAR) model compares different approaches to explain small-scale farmers' decision-making in the context of diversified agroforestry adoption in rural Rwanda. Thereby, it compares random behaviour with perfect rationality (non-discounted and discounted utility maximization), bounded rationality (satisficing heuristic and fast and frugal decision tree heuristic), TPB as a psychological theory, and a regression-based approach. It is aimed at policy-makers, extension agents, NGOs, and cooperatives to better understand how rural farmers decide about implementing innovative agricultural practices such as agroforestry. The model also addresses modelers to support them in selecting an approach to represent human decision-making in ABMs of social-ecological systems. The overall objective is to compare different approaches to explain farmers' agroforestry adoption decision and thereby to provide insights into the implications and explanatory power of selected behavioural approaches. This comparison will contribute to improving forecasts of adoption rates, to supporting the development and implementation of effective interventions that aim to raise low adoption rates, and to understanding what makes strategies successful.

Entities, state variables, and scales

The model comprises three different kinds of agents: farming households, links, and landscape patches. The farming households are the decision-making units in the model and decide about adopting diversified agroforestry systems 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 3.3 in Appendix A. Further household variables describe indicators to calculate farmers' intention, attitude, SN, and PBC in the context of the TPB.

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.

Thirdly, patches represent the models' spatial landscape, e.g. farming plots. Cultivated by the households, patches provide ecosystem services including agricultural outputs. They are described by several variables such as owner, size, and land use, as indicated in table 3.4 in Appendix A.

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.

Process overview and scheduling

Within each year, the model simulates a sequence of activities in the following order (figure 3.2): 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 behavioural specification to achieve robust and stable results.

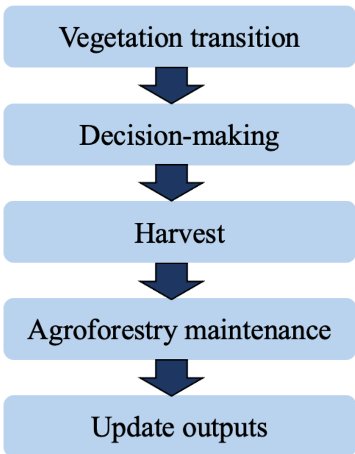

***Figure 3.2**: Process overview*

Design concepts

Theoretical and empirical background

The BASAR model simulates a SES 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 regarding agroforestry adoption. The model includes several behavioural modules to test different approaches to explain 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.

Individual decision-making

Whereas all households initially cultivate wheat and potatoes, they can decide to implement diversified agroforestry over the course of the simulation runs. Decision-making is modelled on the farming household level. Depending on how the different behavioral theories implemented in the simulation model explain decision-making, farmers' objectives, the role of social norms, and uncertainty may differ. The following section presents the alternative behavioural approaches tested in the BASAR model in more detail.

Rational choice theory: Perfectly rational decision-makers are assumed to assess all possible alternatives under perfect information to maximize 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 assume that the decision-maker maximizes a profit function instead (Edwards-Jones, 2006). Furthermore, humans may discount future cash flows (Schlüter et al., 2017). Accordingly, the households calculate the income for each livelihood alternative as follows

$$u_i = -C_0 + \sum_{t=1}^{T} \sum_{j=1}^{J} \frac{price_j * output_{jt} - inputcosts_j - laborcosts_{jt}}{(1+\delta)^t} \qquad 3.1$$

with u_i=utility of household i, t=time, j=agricultural activity, C_0=investment costs in the year of establishment, δ=discount factor. 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", describes a decision process, where the decision-maker sets an aspiration threshold and evaluates possible choices in a random order until an alternative satisfies, e.g. exceeds, the aspiration level (Schilirò, 2018; Simon, 1972). In this application, the households evaluate the livelihoods in a random order and stop searching once they found a solution that exceeds the desired threshold. Farmers consider a livelihood satisfying if it ensures food security, specifically if it provides calories of at least 1830 kcal per family member (Roser and Ritchie, 2013).

Bounded rationality: decision tree: Bounded rationality can also be implemented via a decision tree as a fast and frugal heuristic, where the households evaluate specific criteria in a certain order to decide (Gigerenzer and Goldstein, 1996; Schilirò, 2018). As illustrated in figure 3.3, the decision is initiated by the question whether the farming household suffers from degraded soil, as they indicated in the survey, or whether basic needs cannot be met. Basic requirements are assumed to be satisfied if the agricultural activities provide enough calories to ensure food security. 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 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, the households evaluate whether labour is available. Labour can either be provided by the household members or hired. If all input requirements are fulfilled, the households adopt the agroforestry system.

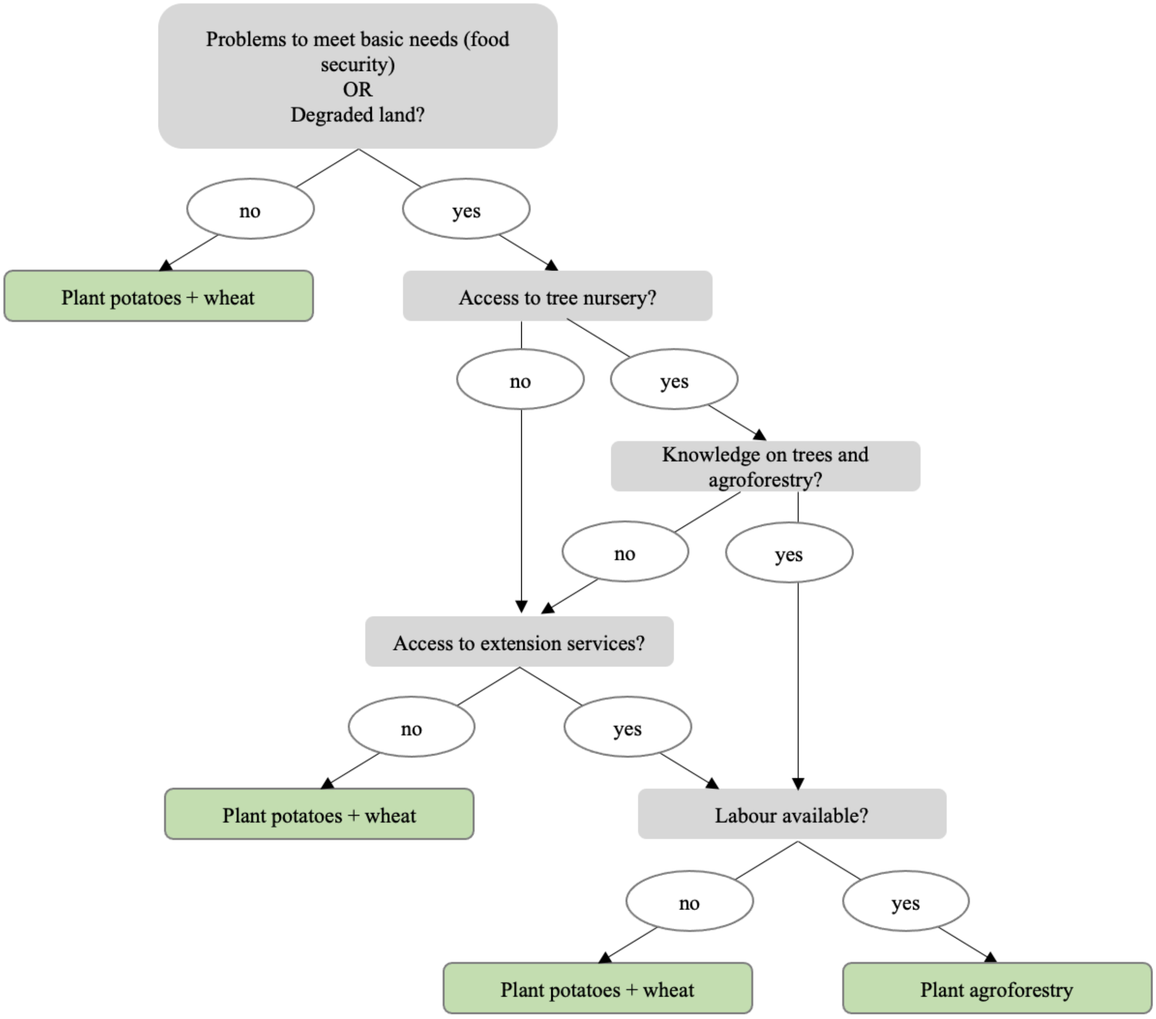

Figure 3.3: *Bounded rationality: decision tree*

Theory of Planned Behaviour: The TPB assumes that deliberative thoughts inform actions as humans consider the implications of their behaviourv (Ajzen, 1991; Scalco et al., 2017). Indicator items based on the household survey data are used to estimate the latent constructs of attitude, SN, PBC, and intention and the relationships thereof via a PLS-SEM. As depicted in figure 3.4, the PLS-SEM demonstrates that attitude is the strongest predictor for intention, but also SN and PBC have a significant influence. In the model, the households compute their individual intention to adopt the diverse agroforestry system according to the following equation

$$Intention_i = w_{Att} * Att_i + w_{SN} * SN_i + w_{PBC} * PBC_i \qquad 3.2$$

with the weights w according to the results of the PLS-SEM. The constructs for attitude and PBC are calculated exclusively based on the survey data. For SN, the share of adopters in the social network is additionally considered and intensifies the perceived norm. Intention is rescaled to lie between 1 and 100 and interpreted as the adoption probability. The Appendix C contains further results regarding descriptive results of the TPB and model evaluation.

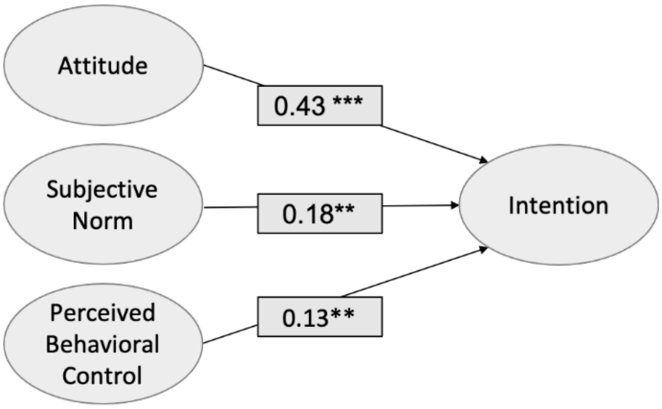

Figure 3.4: *Results: TPB*

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

Econometric: For the econometric approach, a logit model is applied to calculate the probability of a household adopting diverse agroforestry systems based on the household survey as follows

$$P(Y = 1|X = x_i) = \frac{1}{1 + \exp{(x_i^T \beta)}} \qquad 3.3$$

with β=coefficients, x_i=vector of regressors for household i. The regressors displayed in table 3.1 were found to significantly influence the adoption of diverse agroforestry systems in a backwards stepwise regression estimation.

__Table 3.1:__ 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.*

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

Learning

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

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.

Individual prediction

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

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.

Collectives

The agents do not belong to or form collectives.

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.

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.

Observation

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

Details

Implementation details

The model was implemented in NetLogo 6.1.1 (Wilensky, 1999). The model code can be found at https://www.comses.net/codebase-release/55065bfb-08ec-4a15-9357-82797a82e7f0/.

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.

Input Data

A household survey provides data for the parametrization of the farming households (see table 3.3 in the Appendix A). 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 3.5.-3.8 in the Appendix A.

Submodels

The following section describes the submodels, which are performed during each step as illustrated in figure 3.2.

Vegetation transition

In the first step, the landscape agents conduct a vegetation transition. Whereas potatoes and wheats are annual crops, 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. The section “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.

Calibration, verification, and validation

To ensure consistency with reality, model parameters such as household size, prices, and behavioural parameters are based on survey data and secondary data. To assess the accuracy of the programmed model, the code was carefully scanned. Furthermore, we tested corner cases such as extreme points and checked the plausibility of the results (Cooley and Solano, 2011).

Validation to demonstrate the model's fit with the intended application was based on the indirect calibration approach (Windrum et al., 2007). Firstly, patterns were defined with respect to livelihood decisions, which the model was intended to reproduce, e.g. agroforestry adoption rates. Secondly, the submodules, including the different behavioural approaches and ecological processes, were developed based on survey data, theories, econometric methods, and secondary data. Thirdly, the survey results providing empirical evidence on livelihood patterns were used to narrow the parameter space and initial conditions. Further validation involved a RPG that was conducted with 72 of the surveyed farmers and simulated the agroforestry adoption decision. The participants were instructed to make decisions about the land use on their farms as they would in real life. In the game, they had the option to combine crops with different tree species as an alternative to planting only crops. Hence, the decision situation in the game corresponded to the simulated decisions in the model. The agroforestry adoption rate observed in the game was used as a reference pattern to compare it against the simulated adoption rate.

The first three years of the model were compared with farmer behaviour during the game to match the reference period in the RPG.

3.3 Results

The following chapter presents selected descriptive findings of the household survey and simulation results regarding adoption rates and validation against the RPG.

Descriptive results

The descriptive results, presented in table 3.2, provide some general information about the farming households. The low household income with a high dependence on agriculture reflects the living situation of subsistence farmers in rural Rwanda. The survey data shows that households operate on small plots with average farm sizes below one hectare. Only about one third of the farmers state that soil quality of their land is good, which indicates challenges related to soil degradation for the majority of the farmers. Nearly all farmers report some knowledge about agroforestry, either because they implemented it themselves, or learned about it through their social networks, media, or extension services. The prevailing agroforestry systems are dominated by eucalyptus as the main tree species planted on farms. The majority of farmers report that they increasingly experience consequences related to extreme weather events. The Appendix C includes further descriptive results related to the TPB. The TPB findings showed that attitude was relatively high compared to subjective norm and PBC.

Table 3.2: *Selected descriptive results*

Variable	Share / mean value
Respondent is male (in %)	51.03
Age (in years)	39.05 (12.63)
Years of schooling	8.08 (3.77)
Household size	5.87 (2.27)
Annual household income (in RWF)	676,433[1] (745,922)
Share of agricultural income (in %)	68.77 (26.83)
Land size (in ha)	0.94 (1.16)
Land size cultivated (in ha)	0.72 (0.96)
Experience with agroforestry (in %)	98.62
Land quality rated as good (in %)	35.15
Higher frequency of flooding due to extreme weather events perceived (in %)	90.34
Higher frequency of landslides due to extreme weather events perceived (in %)	84.14

Note: Share in percent or mean values are shown. For continuous variables, standard deviations are shown in parentheses.
[1] approximately 670$.

Simulations

The main simulation outcome is the farmers' livelihood choice between adoption of the diversified agroforestry system and cultivation of potato wheat rotations according to the distinct behavioural approaches. The ANOVA demonstrates that selected behavioural approach significantly impact predicted agroforestry adoption rates ($p<0.0001$, Degrees of Freedom (DF)=6, F=10867.66). As figure 3.5 visualizes, the random decision-making module predicts adoption rates of slightly above 50% in the first year. According to the perfect rationality approach, all farmers adopt agroforestry immediately if they apply a non-discounted or a discounted utility function for their decision because agroforestry is more profitable than the potato wheat mix, even when future benefits are discounted.

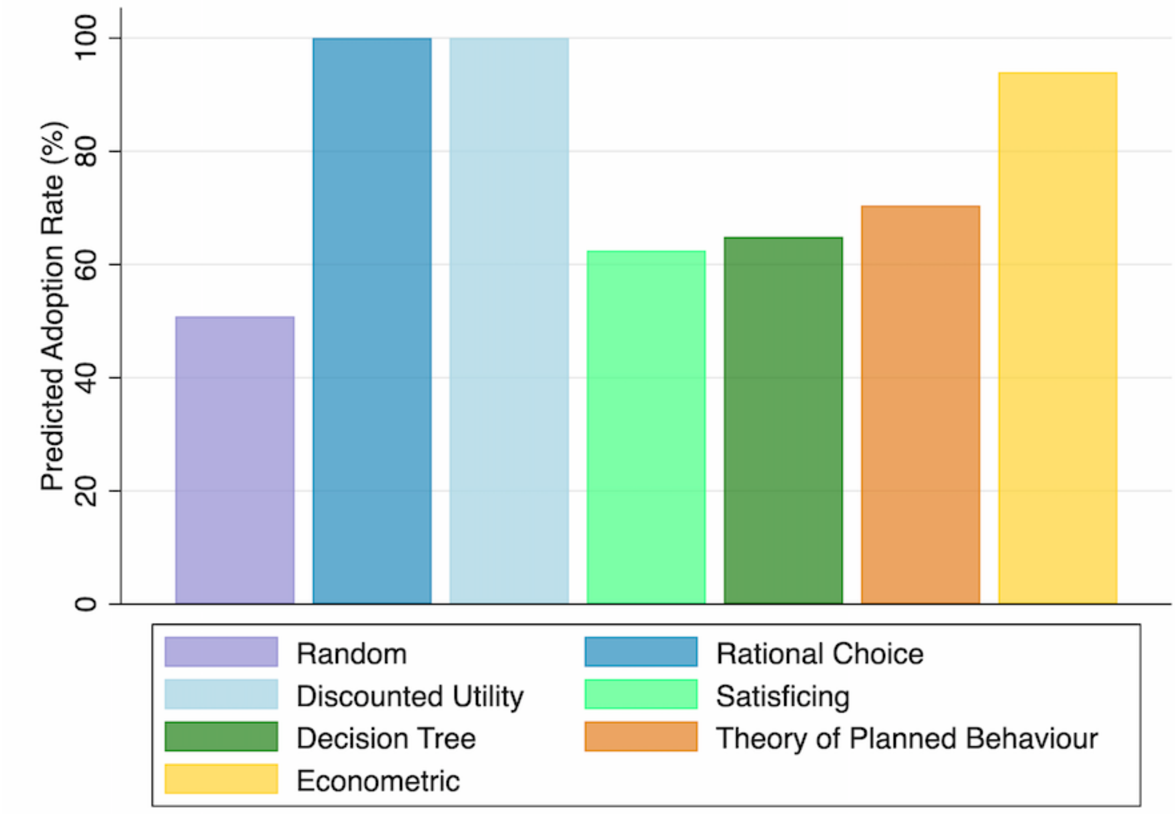

Figure 3.5: *Predicted adoption rates in the first year.*

Note: Blue bars: perfect rationality, green bars: bounded rationality.

Forecasts of bounded rationality result in adoption rates of 62.5% for satisficing farmers and 64.9% if farmers decide based on a decision tree. For satisficing, most households are indifferent between cultivating potato wheat rotations and implementing agroforestry as both options fulfil their financial aspirations. However, for farmers with smaller land area and larger households (and relatively more non-working household members), adopting agroforestry is the only option to achieve their aspired income (13.8% of households), and for farmers with very small plots and a high number of (non-working) household members, not even agroforestry satisfies their needs (10.3%). For the latter group, agroforestry adoption was nevertheless assumed because it is the more profitable alternative. According to the decision tree heuristic, 26.9% of the farmers do not adopt because they can afford to cover their basic needs with traditional wheat potato rotations, and they do not report degraded land. 6.8% cannot access extension services and thus lack the necessary inputs to adopt.

The TPB predicts that 70.4% of the farmers adopt the agroforestry system in the first year. Thereby, attitude is the strongest driver for adoption, as attitude generally is quite high on the one hand and has the highest influence on intention on the other. According to the PLS-SEM results, attitude itself is driven by financial motives (increased income), but also decreased soil erosion, protection of environmental health, climate change mitigation, increased animal species diversity, and improved tourism significantly influence attitude. SN also positively impacts intention and is mainly influenced by the family's opinion and to a smaller extent also by friends' views. PBC has the smallest, yet significant influence on intention amongst the three constructs. Here, PBC increases if the farmers think they can control adoption themselves and implement agroforestry despite possible obstacles.

Lastly, the logit model predicts adoption rates of 93.9%. Here, land size influences the likelihood of adoption to the largest extent with greater farm sizes being positively associated with adoption. Having degraded land and valuing biodiversity in general increases the adoption probability. Whereas household size has a positive influence, the dependency ratio decreases the likelihood of implementing diverse trees on farms.

As figure 3.6 visualizes, the share of adopters according to the different behavioural approaches followes different paths over time. In particular, perfect rational farmers adopt in the first year. Because they optimized their decision, they do not revise it, and the adoption rate remains constant. Individuals who base their behaviour on a decision tree also do not deviate from their choice as their needs do not change and inputs do not become available after a certain point in time if farmers cannot access them initially. In contrast, other decision modules including random choice, satisficing, econometrics, and TPB involve random elements and are repeated over time. Thus, they can lead to adoption at later points in time as well. Furthermore, if the TPB is assumed as the underlying decision process, the SN increases pressure to adopt over time as more farmers in the social network implement agroforestry. Overall, the ANOVA confirms that not only the decision module, but also time significantly impacts the share of adopters ($p<0.0001$, $DF=35$, $F=3418.00$). The Appendix D contains further simulation findings related to the resulting income and aggregated effects on the area under agroforestry.

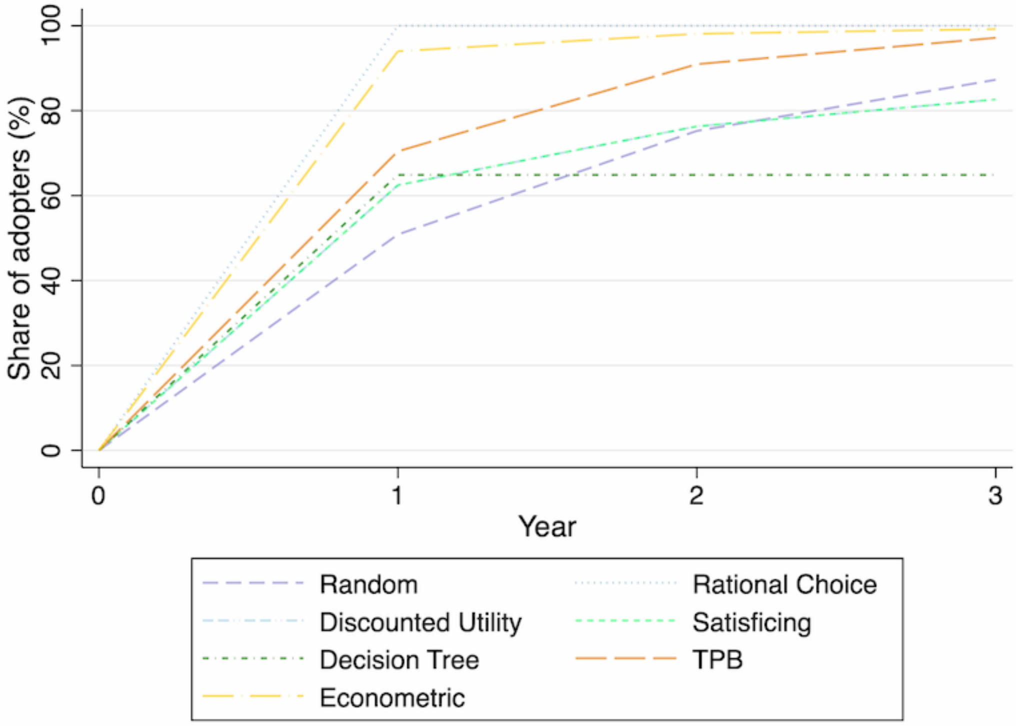

Figure 3.6: *Adoption curves over the first three years.*

Note: Blue lines: perfect rationality, green lines: bounded rationality.

Validation

The simulations are validated against a RPG that simulated a situation in which the farmers make decisions about adopting diversified agroforestry systems on their fields. According to the RPG, 89.6% of the farmers adopt diverse agroforestry within the first three years, as figure 3.7 illustrates. Hence, the forecasts according to the TPB, which predict adoption rates of 86.2% over the first three years, coincide with the RPG to the largest extent among the investigated approaches. The econometric approach computes similar adoption rates with 97.1%, but slightly overestimates forecasts compared to the RPG. Perfect rationality with a discounted and non-discounted utility function both overestimate adoption, and the two bounded rational heuristics underpredict adoption during the first three years with rates of 73.8% (satisficing) and 64.9% (decision tree) compared to the RPG. Thereby, the decision tree heuristic is even outperformed by random decision-making, which resulted in predicted adoption by 71.1% of the farmers over the first three years.

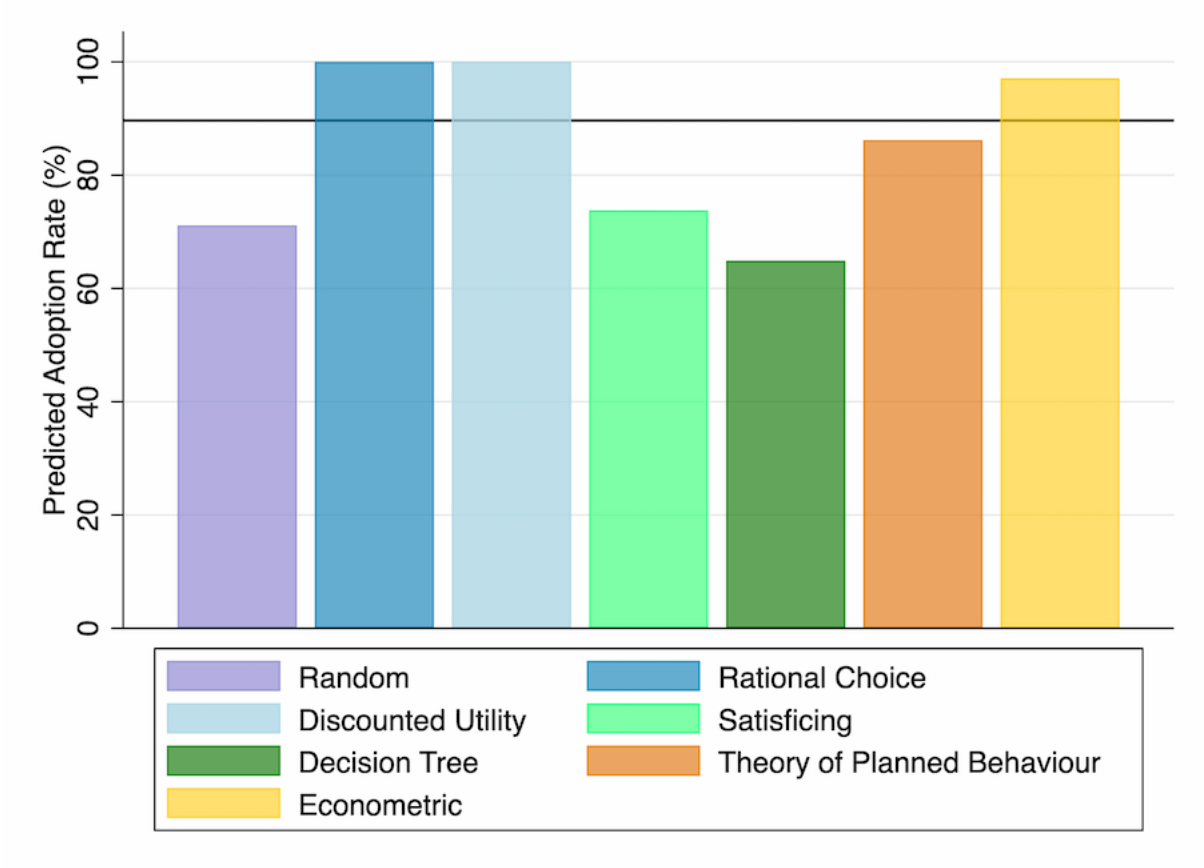

Figure 3.7: *Validation of predicted adoption rates against the RPG for the first three years.*

Note: Blue bars: perfect rationality, green bars: bounded rationality, black line: adoption rate as observed in the RPG.

After the RPG, the participating farmers were asked about the strategies they applied during the game (Appendix B). All farmers stated that profit played a major role for their behaviour. About one quarter of the players further stated that biodiversity conservation influenced their actions. For about 50% of the farmers, environmental protection was a significant driver for their behaviour. None of the farmers implemented a random strategy or tried to imitate their co-players. A sensitivity analysis demonstrated that results remain robust towards variations of 25% in prices or output quantities.

3.4. Discussion

This study compares different explanations of farmers' decision to adopt diversified agroforestry and their influence on agroforestry adoption rates. The investigated behavioural approaches differed regarding their focus and aspects they account for. The agent-based simulations showed that the explanation of agents' decision to implement diversified agroforestry strongly influenced predicted adoption rates.

Rational choice theory

The simulation results revealed that all non-discounting and discounting rational actors adopt diversified agroforestry. Rational choice theory, implemented as utility or profit maximization, is a popular approach to explain farmers' decision-making, particularly in economic applications (Groeneveld et al., 2017; Reidsma et al., 2018). In line with these results, several authors conclude that income can be a major incentive for adopting agricultural innovations such as agroforestry, and that farmers consider trees on farms as "savings accounts" for the next generation (Cedamon et al., 2018; Mukuralinda et al., 2016; Oduro et al., 2018; Staton et al., 2022). Also, farmers participating in the RPG reported that financial motives influenced their adoption decisions. Consequently, financial aspects are important to capture and forecast the rate and scale of adoption (Robinson and Rai, 2015). Our results indicate that rational choice theory with discounted and non-discounted utility functions predicts very high adoption rates. In particular, all farmers decide to adopt the most profitable land use in the first year without deviating from their optimal choice over time. Also, other authors report that rational farmers are reactive and choose the best economic alternatives immediately (Cabrera et al., 2010; Lindgren and Elmquist, 2005; Mialhe et al., 2012). Despite its widespread use, rational choice theory and its implementation of farmers as rational profit maximisers has been criticized because it entails strong assumptions (Gigerenzer and Goldstein, 1996; Simon, 1955). The first assumption is that income is the exclusive motivation for farmers. However, research shows that other factors also impact adoption, such as farmer and household characteristics, social capital, and traits of the innovation itself (Edwards-Jones, 2006; Rogers, 1983). Secondly, rational choice theory assumes that decision-makers are omniscient with respect to the environment and that their preferences are well behaved, i.e., are ordered and exhibit transitivity properties (Kennedy, 2012). However, in reality, the human ability to take deliberate actions is restricted by cognitive limitations, and, thus, individuals usually do not conduct a complete evaluation of available alternatives to maximize profits in a fully rational manner (Gigerenzer and Goldstein, 1996; Kennedy, 2012; Simon, 1972). Consequently, purely financially motivated rational decision-making might be unrealistic (Gigerenzer and Goldstein, 1996; Meijer et al., 2015b; Simon, 1972). In accordance with this criticism, validating the simulation results against the RPG shows that full rationality overestimats adoption as it predicts full adoption, which also contrasts the frequently observed low uptake of agricultural innovations (Do et al., 2020; Macours, 2019). Thus, approaches based on full rationality seem to be limited in their ability to explain decision-making on the farm-level (Edwards-Jones, 2006).

Bounded rationality

As an alternative to rational choice theory, the bounded rationality approach has been developed, which accounts for cognitive limitations in the human ability to take deliberate action (Gigerenzer and Goldstein, 1996; Kennedy, 2012; Simon, 1972; Todd and Gigerenzer, 2000). In this study, we implemented a fast and frugal decision tree heuristic and a satisficing behaviour as theories of bounded rationality. According to the simulation results, satisficing farmers adopt agroforestry in 62.5% of the cases. Thereby, the majority of satisficing farmers with larger farm sizes can generate their aspired income either via potato wheat rotation or by agroforestry cultivation and are hence indifferent between these alternatives. This result shows that the satisficing routine as a non-optimizing behaviour restricts adoption (Holtz and Nebel, 2014). From a methodological perspective, the satisficing heuristic demonstrates how bounded rational models can incorporate heterogeneity as intrinsic propensities to adopt, e.g. through individual utility aspiration thresholds (Kiesling et al., 2012).

According to the decision tree heuristic, the main reasons for non-adoption, which applied to 26.9% of the farmers, includes adequate land quality and the opportunity to ensure household food security through potato wheat cultivation. Some farmers were unable to adopt due to unavailability of extension services and farming inputs. Thus, the decision tree identifies external factors which limit adoption and confirms that incentives such as input provision and capacity training can support on-farm tree planting (Oduro et al., 2018). Thereby, this heuristic illustrates that bounded rationality focuses on the process of decision-making rather than the goal of profit maximization and is therefore not a black box (Cabrera et al., 2010). Our simulations demonstrate that bounded rational agents are less likely to adopt the agricultural innovation compared to the RPG, and even less likely than perfectly rational agents. Thereby, our results confirm the findings of other authors who report different outcomes for rational and bounded rational behaviour (Schindler, 2013; van Duinen et al., 2016). In contrast to the simulation results, other authors conclude that deviation from perfect rationality improves the model's explanatory power (Holtz and Nebel, 2014; Richetin et al., 2009). However, bounded rational models have been criticized because they can seem as "ad-hoc" solutions and various approaches are available to express bounded rational behaviour (An, 2012; Malawska and Topping, 2016; Zhang and Vorobeychik, 2019). Also in this application, the two approaches of bounded rationality differ strongly with respect to their implementation. Moreover, bounded rational heuristics require further knowledge about how decision-making changes as a response to a policy intervention or environmental changes (Schreinemachers and Berger, 2006). Overall, utility maximization may be suitable to explain decision-making in applications, where profit-oriented agents have full access to information and adequate opportunities to process them. In contrast, heuristic methods may better reflect human decision-making with limited cognitive abilities or when single parameters are decisive and cannot be outweighed by other factors (Cabrera et al., 2010; Schindler, 2013).

TPB

The TPB predicts that 70.4% of the farmers adopted in the first year with a rising number of adopters over time. In this application, attitude is the strongest driver for adoption. Several authors find attitude to significantly influence farmers' intention to adopt agroforestry (Buyinza et al., 2020a, 2020b; McGinty et al., 2008; Meijer et al., 2015b). Here, attitude itself is driven by financial considerations, concern for environmental protection, climate change mitigation, enhanced animal species diversity, improved tourism, and avoidance of soil erosion. This suggests an intrinsic motivation of the farmers to protect the environment and biodiversity in addition to financial ambitions. This result coincides with the high share of farmers who reported that environmental protection and biodiversity conservation motivated them to plant on-farm trees in the RPG. SN is also positively associated with intention. Therefore, our research is in line with other authors who find that SN significantly impacts the intention to adopt agroforestry of farmers who rely on their social networks to drive change within the community (Buyinza et al., 2020b). The relatively low influence of SN found here coincides with the result that SN is commonly the weakest predictor of intention (Armitage and Conner, 2001). In the present model, the impact of SN is dynamic, and the non-adopting farmers experience higher pressure as more farmers in their social networks adopt over time. Whereas here the network posed the SN, social network effects can also contribute to information sharing amongst farmers and speed up the diffusion process in this way (Beyene and Kassie, 2015; Khataza et al., 2018). Also, PBC impacts intention in this application. This result supports other results of other authors who find a significant role of PBC for agroforestry adoption (Buyinza et al., 2020a, 2020b; McGinty et al., 2008).

The TPB forecasts are most similar to those observed in the RPG among the approaches investigated in this study. This high validity suggests high explanatory and predictive power of the TPB and highlights the important role of SN, PBC, and especially attitude for agroforestry adoption. Because attitude is not only driven by financial motivations, but also ecological concerns for example, other theories that focus exclusively on profits are unlikely to completely capture farmers' preferences and hence the true underlying decision-making process. Along these lines, several authors highlight the potential of the TPB to explain sustainable and pro-environmental behaviours such as agroforestry adoption due to the inclusion of social and psychological aspects as key drivers of the farmers' decision-making process (Buyinza et al., 2020a; Groeneveld et al., 2017; Maleksaeidi and Keshavarz, 2019; Scalco et al., 2018). Compared with other behavioural approaches, the three TPB-constructs mediate many relevant determinants implemented as background factors in other theories and accounts for additional factors such as the perceived ability to perform the action (Maleksaeidi and Keshavarz, 2019; Schrieks et al., 2021).

Despite the wide-ranging application opportunities, the TPB has been criticized for several reasons. Firstly, in addition to the determinants of intention proposed by the TPB, other factors such as knowledge can influence human decisions (Maleksaeidi and Keshavarz, 2019). However, the TPB can be flexibly extended to increase its explanatory power (Chen, 2016). As a robustness check, we included knowledge as a further determinant of intention, but it did not exert a significant influence. Secondly, the TPB has been criticized to be more suited to explain comparatively deliberate actions (Kan et al., 2020). On-farm cultivation of trees poses a long-term investment for small-scale farmers and is thus likely a deliberate measure. In general, the prediction of intention depends on the specific behaviour and context (Ajzen, 1991; Buyinza et al., 2020b), but the TPB demonstrates promising results to explain behavioural intentions in this context.

Econometric approach

The econometric results showed that land and household size, available labour, and soil quality determine whether a household adopts agroforestry, which also other authors report (Gebru et al., 2019; Mekonnen and Damte, 2011; Mfitumukiza et al., 2017; Sanou et al., 2019; Sood and Mitchell, 2009). Additionally, a general valuation of biodiversity increases adoption likelihood in this application, which suggests intrinsic motivations. Further determinants which do not significantly influence agroforestry adoption in our study region, but in other applications include age, gender, and education of the household head, risk attitude, social capital, market distance, and location (Cedamon et al., 2018; Deressa et al., 2009; Gebru et al., 2019; Khan et al., 2017; Mekonnen and Damte, 2011; Mfitumukiza et al., 2017).

By directly linking farmer characteristics with land use decisions as reported in a survey, this empirically-oriented tool computes individual adoption probabilities and is therefore able to capture farmer heterogeneity (Evans et al., 2006; Kiesling et al., 2012). Furthermore, econometric estimation of choice probabilities provides a method for parameterization based on empirical data, which practical applications and policy analyses frequently require (Kiesling et al., 2012). However, econometric results reveal information regarding correlations rather than causations, and therefore insights into the actual underlying causal mechanisms, motivations, or preferences driving the decision-making process are limited (An, 2012; Kiesling et al., 2012; Villamor et al., 2012). Despite the limited explanatory power, the results suggest that an econometric-based specification of farmer behaviour appears promising for forecasting as this approach predicts similar, albeit slightly higher adoption rates compared to the RPG in this application.

Policy implications

Different explanations for human behaviour in simulation models do not only lead to divergent adoption rates, but they also differ regarding their policy implications. Assuming a profit maximizer in line with the rational choice theory implies that farmers base their decisions exclusively on profits. Consequently, financial incentives such as subsidies or payment for ecosystem services should motivate farmers. Thereby, financial incentives need to be sufficiently high to compensate for opportunity costs and account for the initial investment as well as the time span until trees realize benefits (Do et al., 2020; Piñeiro et al., 2020; Staton et al., 2022). Financial incentives can provide effective measure also if a satisficing heuristic explains farmers' decision-making process: if the promoted livelihood alternative does not exceed the aspiration threshold, financial incentives can increase attractiveness of the option promoted by policy-makers, extension agents, or cooperatives. However, in this application both alternatives satisfy the aspired income level for the majority of the satisficing agents, and perfect rationality predicts full adoption. Thus, a financial intervention would have very limited effects if these approaches would truly explain behaviour.

The fast and frugal decision tree heuristic demonstrates that farmers may abstain from adoption because they do not consider agroforestry as necessary. Thus, increasing awareness of benefits, especially with respect to income, soil fertilization, and protection against soil erosion, could stimulate demand. Hence, a possible intervention could disseminate information about the advantages of agroforestry. Furthermore, this heuristic implies that access to inputs such as knowledge and seedlings pose adoption barriers. Thus, lifting external barriers by providing inputs such as seedlings and information and making extension services available offers a promising pathway to support farmers' adoption if the decision tree heuristic would explain farmers' behaviour.

The TPB, in line with the econometric approach and decision tree heuristic, also implies that attitude and recognition of ecological benefits play a crucial role for adoption. Attitude as the strongest driver of intention is influenced by income, but also environmental health, increased animal species diversity, climate change mitigation, decreased soil erosion, and enhanced tourism, as the PLS-SEM revealed. Consequently, spreading awareness about environmental benefits, for example through extension programs, trainings, or information campaigns, is likely to improve farmers' perception of ecological benefits and hence intention to adopt. Because the SN also significantly influences intention, targeting social networks, particularly farmers' friends and families, could be used to intensify social influence (Proestakis et al., 2018). Also, PBC significantly correlates with intention, which implies the need to remove external barriers by providing inputs such as seedlings and trainings, as also the decision tree heuristic implies.

Lastly, although the econometric model does not directly focus on explaining of the decision-making process itself, insights regarding correlations can nevertheless support policy design. According to the logit regression, farmers with smaller land sizes are less likely to adopt. This suggests that these farmers face obstacles and hence require special support. As reportedly poor quality soil negatively influences adoption, interventions should spread information about benefits of agroforestry, especially with respect to land quality and soil erosion protection. Also, household size and dependency ratio significantly impact adoption. Consequently, promoting agroforestry technologies that require less labour input could help farmers to use their labour more efficiently, thereby overcoming adoption barriers. The positive correlation between farmers' valuation of biodiversity and adoption likelihood supports the finding that farmers are intrinsically motivated to adopt biodiversity-enhancing agricultural practices. Because several of the investigated approaches provide evidence that non-financial factors are involved in farmers' motivation to plant on-farm trees, the effects of financial instruments should be carefully evaluated to reduce the risk of crowding out intrinsic motivations (James, 2005; Piñeiro et al., 2020).
Overall, the findings suggest that educating farmers about agroforestry-related benefits, lifting external barriers, and possibly creating financial incentives offer promising pathways to raise

agroforestry adoption rates. Yet, the various decision-making approaches led to distinct policy implications in some cases. This highlights the importance to adequately explain human behaviour for designing and implementing successful interventions.

Limitations and Future Research

The study has several limitations. First of all, household choices are assumed to be time-consistent without switching between decision-making modules. However, several authors suggests that human decision-making may be time-inconsistent, culture- and context-dependent, and vary between individuals (Desmarchelier and Fang, 2016; Jager and Janssen, 2012; Malawska et al., 2014). The present model focuses on a specific biodiversity-enhancing agroforestry system in rural Rwanda. Hence, the results and implications provide insights related to the case study, but might differ in other contexts. The findings might not apply if the decision relates to other farming practices, concerns a smaller period of time, or is based on habits. Another limitation of this study is given by the selection of commonly used approaches for comparison. Further practical issues including social status, influence of opinion leaders, and logistics such as access to stable markets are not accounted for. The model does not consider whether farmers already cultivate trees with similar purposes on the farms, which might influence the adoption decision as well. The behavioural module is restricted to the two livelihood alternatives. Thereby, the model makes implicit or explicit assumptions regarding farmers' preferences and goals. Also, ecological processes are modelled in a simplified manner. Regarding the practical implementation of the behavioural module, several options might exist to operationalize a single approach when coding it into a modelling software (Muelder and Filatova, 2018). Another limitation concerns the validation of the study: the different approaches were validated against a RPG, but real-world observations are not available.

These limitations can stimulate further research. More complex and sophisticated decision rules combining or adding new theories may be considered for further analysis. Also, alterations and extensions of the already investigated modules could be interesting, such as the inclusion of computational costs for information search or the model of Goal-directed Behaviour as an expansion of the TPB to include affective, motivational, and automatic processes (Petitet et al., 2021; Richetin et al., 2010). Future research would benefit from assessing changes in external as well as internal decision-making parameters or switching of behavioural rules (Jager and Janssen, 2012). Another focus of future work could be to investigate the consequences of different behavioural approaches under changing conditions, for example by introducing a climate change scenario. Furthermore, future studies could implement the same methodology to validate the results across different contexts, such as other regions or farming practices. Meta-analyses could then be conducted to compare these findings and validate if one approach is best suited for a particular context. Lastly, in addition to the methodology used in this study, researchers could implement psychological experiments to compare the behavioural approaches.

3.5. Summary and Conclusions

The present study compared selected behavioural approaches to explain farmers' decision to adopt diversified agroforestry. An agent-based simulation model was applied to a case study in rural Rwanda to investigate small-scale farmers' decision to adopt a biodiversity-enhancing agroforestry system combining potatoes and wheat with trees of *Grevillea robusta*, *Alnus acuminata*, and *Markhamia lutea.* The agent-based simulation model compared random adoption with perfect rationality implemented as non-discounted and discounted utility maximization, bounded rationality implemented via a satisficing heuristic and a fast and frugal decision tree, the TPB, and an econometric approach. The simulations demonstrated that the assumed explanation for farmer behaviour significantly impacted predicted adoption rates. Thus, the results highlight that assuming a behavioural approach to explain decision-making has important implications. Among the investigated approaches, the TPB-based simulations predicted adoption rates most similar to those observed in a RPG, which was conducted for validation. This result implies that intrinsic factors such as attitude and more specifically concern for environmental health and climate change mitigation in addition to income are important drivers of farmers' decisions. Thus, these factors play an important role for adoption behaviour and should be accounted for by the approach selected to explain decision-making. The selected explanation of farmers' behaviour in the model also influenced derived policy recommendations. In this context, educating about benefits of agroforestry and promoting a positive attitude in addition to financial incentives appear as promising interventions to raise low agroforestry adoption rates of small-scale farmers.

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Appendix A: Agent-based Simulation Model

Table 3.3: *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 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 (S
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
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.

Table 3.4: *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

Table 3.5: *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)
Fertilizer (NPK)	300 Kg/ha	180900	Ministry of Environment – Rwanda (2020); ESoko (2021)
Pesticides	RWF/ha	17059	Mugabo et al. (2007)

Table 3.6: *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 3.7: Agroforestry system: tree inputs

Input	Unit	Quantity/cost	Time	Reference
Seedlings	piece	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 3.8: 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.

Appendix B: Further Descriptive Results

Table 3.9: *Strategies according to the RPG*

Objective	**Share of players** (in %)
Profit maximization	100
Increase biodiversity	27.78
Protect the environment	51.39
Imitate others	0
Random	0

Appendix C:

Survey Data for Analysing Farmers' Intention to Adopt Agroforestry in Rural Rwanda: a Partial Least Squares Structural Equation Modelling (PLS-SEM) Approach

This Appendix section is submitted to:

Data in Brief

Abstract

This article presents raw and analysed survey data that determine the influence of socio-cognitive factors on small-scale farmers' intention to adopt diversified agroforestry systems in rural Rwanda. The data were collected through face-to-face interviews conducted in October and November 2020. Respondents included 145 small-scale farmers, which were randomly sampled from three sectors in Western Province of Rwanda. The first part of the structured questionnaire included questions on farmers' sociodemographic characteristics and agricultural activities. The design of the second part was based on the Theory of Planned Behaviour (TPB). It consisted of indicators questions related to this theory including farmers' intention, attitude, subjective norm, perceived behavioural control, and knowledge regarding adopting diversified agroforestry. Additional to descriptive analysis, a partially least squares structural equation model (PLS-SEM) was applied using the software SmartPLS version 3. The SEM path coefficients showed positive relationships of farmers' attitude, subjective norm, and perceived behavioural control with their intention to adopt diversified agroforestry. The data are important for understanding the intrinsic drivers of farmers' agroforestry adoption behaviour. It can provide insights for researchers and policy-makers interested in explaining and predicting farmers' adoption decisions. The insights can inform the design and implementation of interventions that aim to support farmers' adoption of agroforestry as a sustainable agricultural practice.

Keywords

Theory of Planned Behaviour, Intention, Decision-making, Innovation Adoption, Small-scale Agriculture

Table 3.10: *Specifications table*

Subject	Agricultural Economics
Specific subject area	Agroforestry adoption in small-scale agriculture of developing countries, theory of planned behaviour, socio-cognitive drivers
Type of data	Tables Figure
How the data were acquired	Data were collected through face-to-face interviews with smallholder farmers using tablet-based questionnaires. Farmers' responses to the structured questions were entered into the software Open Data Kit (ODK). Data analysis was performed using the software Stata 16 and SmartPLS version 3.
Data format	Raw Analysed
Description of data collection	For the survey, 48 to 49 small-scale farmers with age ≥ 18 years were randomly sampled from each of the three sectors in the case study area, comprising a total sample of 145 farmers. Face-to-face interviews took place in October and November 2020 and were administered in Kinyarwanda language. The English version of the structured questionnaire is provided as a supplementary file.
Data source location	• Sectors: Karago, Jenda, and Nyundo • Country: Rwanda
Data accessibility	Repository name: Mendeley Data Data identification number: http://dx.doi.org/10.17632/3cr62m8wj9.1 Direct URL to data: https://data.mendeley.com/v1/datasets/3cr62m8wj9/draft?preview=1
Related research article	B. Noeldeke, E. Winter, E. B Ntawuhiganayo, Explaining Agroforestry Adoption in Rural Rwanda: an Agent-based Simulation Study of Human Decision-making, Ecol. Econ. Under review.

Value of the data

- The data presents the impact of attitude, subjective norm, and perceived behavioural control on farmers' intention to adopt diversified agroforestry systems. The data contributes to identifying intrinsic drivers of farmers' adoption behaviour.
- The data benefits stakeholders including policy-makers, NGO's, extension officers and practitioners as it offers an improved understanding of farmers' adoption decision-making processes.
- The data provides insights for practitioners and researchers who are interested in understanding, explaining, or predicting agroforestry adoption rates.
- This data can be used to identify entry points for policy interventions based on the socio-cognitive drivers to motivate agroforestry adoption, contributing to the promotion of more sustainable agricultural practices in developing countries such as Rwanda.

Data description

The dataset examines small-scale farmers' intentions to adopt diversified agroforestry systems in rural Rwanda. The data were collected through a two-part questionnaire. The first part addressed farmers' socio-demographic characteristics and agricultural activities including gender, age, land size, and previous experience with agroforestry. Table 3.11 presents descriptive results related to this survey part. The second survey section included questions related to factors influencing farmers' intention to plant diverse tree species on their farms based on the Theory of Planned Behaviour (TPB). According to the TPB, behaviour directly results from intention, which in turn is formed by attitude, subjective norms, and perceived behavioural control related to the respective behaviour [1]. Extending the original TPB, the data set additionally includes knowledge as an antecedent of intention. Thus, the dataset contains information on behavioural beliefs and subjective evaluation to estimate attitude (table 3.12), normative beliefs and motivation to comply to estimate subjective norm (table 3.13), control beliefs and perceived power over these beliefs to estimate perceived behavioural control (table 3.14), required knowledge and personal knowledge status to estimate knowledge (table 3.15) and farmers' intention to cultivate diverse tree species on their farms (table 3.16). The questionnaire in English is included in the supplementary materials. The raw data associated with the dataset comprise the individual respondents' answers. The data were analysed using a PLS-SEM. Figure 3.8 illustrates the PLS-SEM results of the model with attitude, subjective norm, and perceived behavioural control, which are the constructs that significantly influence farmers' intention to adopt diversified agroforestry in this context.

Table 3.11: *Selected descriptive results*

Variable	Share / mean value
Respondent is male (in %)	51.03
Age (in years)	39.05 (12.63)
Years of schooling	8.08 (3.77)
Household size	5.87 (2.27)
Annual household income (in Rwandan franc)	676,433[1] (745,922)
Share of agricultural income (in %)	68.77 (26.83)
Land size (in ha)	0.94 (1.16)
Land size cultivated (in ha)	0.72 (0.96)
Experience with agroforestry (in %)	98.62
Land quality rated as good (in %)	35.15
Higher frequency of flooding due to extreme weather events perceived (in %)	90.34
Higher frequency of landslides due to extreme weather events perceived (in %)	84.14

Note: *n*=145. Percentage share or mean values are shown. For continuous variables, standard deviations are shown in parentheses.
[1] approximately 670 US-Dollar.

Table 3.12: *Theory of Planned Behaviour: Attitude*

	Attitude	Mean	SD	Min	Max
1a	Planting different tree species on farms will improve the health of the environment. *(1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly agree)*	4.359	0.523	3	5
1b	For you, improving environmental health is… *(1=Extremely bad, 2=Bad, 3=Neither bad nor good, 4=Good, 5=Extremely good)*	4.414	0.535	3	5
2a	Planting different tree species on farms will increase income. *(1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly agree)*	4.469	0.553	2	5
2b	For you to have more income is … *(1=Extremely bad, 2=Bad, 3=Neither bad nor good, 4=Good, 5=Extremely good)*	4.552	0.539	2	5
3a	Planting different tree species on farms will increase the availability of timber. *(1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly agree)*	4.152	0.861	2	5
3b	For you to have more timber is … *(1=Extremely bad, 2=Bad, 3=Neither bad nor good, 4=Good, 5=Extremely good)*	4.186	0.842	2	5
4a	Planting different tree species on farms will increase the availability of fruits. *(1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly agree)*	4.186	0.773	2	5
4b	For you to have more fruits is … *(1=Extremely bad, 2=Bad, 3=Neither bad nor good, 4=Good, 5=Extremely good)*	4.29	0.799	2	5
5a	Planting different tree species on farms will improve soil fertility. *(1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly agree)*	4.352	0.672	2	5
5b	For you, improved soil fertility is … *(1=Extremely bad, 2=Bad, 3=Neither bad nor good, 4=Good, 5=Extremely good)*	4.469	0.624	2	5
6a	Planting different tree species on farms will decrease soil erosion. *(1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly agree)*	4.69	0.464	4	5

6b	For you, decreased soil erosion is … *(1=Extremely bad, 2=Bad, 3=Neither bad nor good, 4=Good, 5=Extremely good)*	4.662	0.475	4	5
7a	Planting different tree species on farms will improve pest control. *(1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly agree)*	3.614	0.81	1	5
7b	For you, improved pest control is … *(1=Extremely bad, 2=Bad, 3=Neither bad nor good, 4=Good, 5=Extremely good)*	3.814	0.726	2	5
8a	Planting different tree species on farms will increase pollination and crop yield. *(1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly agree)*	3.821	0.723	2	5
8b	For you, higher pollination and crop yield are … *(1=Extremely bad, 2=Bad, 3=Neither bad nor good, 4=Good, 5=Extremely good)*	3.821	0.796	2	5
9a	Planting different tree species on farms mitigates climate change. *(1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly agree)*	4.166	0.646	1	5
9b	For you, mitigated climate change is … *(1=Extremely bad, 2=Bad, 3=Neither bad nor good, 4=Good, 5=Extremely good)*	4.172	0.605	3	5
10a	Planting different tree species on farms increases the diversity of animal species. *(1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly agree)*	3.828	0.828	2	5
10b	For you, increased diversity of animal species is … *(1=Extremely bad, 2=Bad, 3=Neither bad nor good, 4=Good, 5=Extremely good)*	3.71	0.905	2	5
11a	Planting different tree species on farms enhances tourism. *(1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly agree)*	4.034	0.711	2	5
11b	For you, enhanced tourism is … *(1=Extremely bad, 2=Bad, 3=Neither bad nor good, 4=Good, 5=Extremely good)*	4.028	0.726	2	5

Note: n=145.

Table 3.13: *Theory of Planned Behaviour: Subjective Norm*

	Subjective Norm	Mean	SD	Min	Max
12a	Your family thinks you should plant different tree species on your land. *(1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly agree)*	4.269	0.615	2	5
12b	Generally speaking, you want to do what your family thinks you should do. *(1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly agree)*	4.255	0.598	2	5
13a	Your friends think you should plant different tree species. *(1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly agree)*	3.91	0.655	2	5
13b	Generally speaking, you want to do what your friends think you should do. *(1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly agree)*	3.738	0.808	1	5
14a	Other farmers think you should plant different tree species. *(1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly agree)*	3.917	0.534	2	5
14b	Generally speaking, you want to do what the other farmers think you should do. *(1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly agree)*	3.869	0.648	2	5
15a	Your cooperative thinks you should plant different tree species. *(1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly agree)*	3.303	1.18	1	5
15b	Generally speaking, you want to do what your cooperative thinks you should do. *(1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly agree)*	3.366	1.166	1	5
16a	Your village head thinks you should plant different tree species on your land. *(1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly agree)*	3.766	0.745	2	5
16b	Generally speaking, you want to do what your village head thinks you should do. *(1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly agree)*	3.745	0.724	2	5

17a	The extension officer thinks you should plant different tree species on your land. *(1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly agree)*	4.048	0.605	2	5
17b	Generally speaking, you want to do what your extension officer thinks you should do. *(1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly agree)*	4.083	0.583	2	5
18a	The community values different tree species. *(1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly agree)*	3.945	0.537	2	5
18b	Generally speaking, it is important to you to conform with the community's values. *(1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly agree)*	3.883	0.64	2	5

Note: *n*=145.

Table 3.14: *Theory of Planned Behaviour: Control Beliefs*

	Control Beliefs	Mean	SD	Min	Max
19a	Planting different tree species is controlled by the farmers themselves. *(1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly agree)*	3.821	0.752	1	5
19b	You personally are able and confident to plant different tree species on your farm. *(1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly agree)*	4.041	0.676	2	5
20a	Planting different tree species requires resources such as time, seedlings, land, labor, financial capital, knowledge, and skills. *(1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly agree)*	4.014	0.677	2	5
20b	You have the resources (time, seedlings, land, labor, financial capital, knowledge, and skills) to plant different tree species on your farm. *(1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly agree)*	3.193	0.952	1	5
21a	Planting different tree species is doable despite possible obstacles (such as extreme weather events, lack of institutional support, insufficient knowledge, lack of land, unavailability of seedlings). *(1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly agree)*	3.724	0.759	1	5
21b	If you encountered obstacles such as extreme weather events, lack of institutional support, insufficient knowledge, lack of land, or unavailability of seedlings you would feel confident to plant different tree species on your farm nevertheless. *(1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly agree)*	3.614	0.843	1	5

Note: *n*=145.

Table 3.15: *Theory of Planned Behaviour: Knowledge*

	Knowledge	Mean	SD	Min	Max
23a	Planting different tree species requires knowledge about tree management. *(1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly agree)*	4.055	0.587	2	5
23b	You have knowledge about tree management. *(1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly agree)*	3.207	0.971	2	5
24a	Planting different tree species requires knowledge about agroforestry. *(1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly agree)*	3.993	0.479	2	5
24b	You have knowledge about agroforestry. *(1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly agree)*	3.117	0.997	1	5
25a	Planting different tree species requires knowledge about biodiversity. *(1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly agree)*	3.628	0.726	1	5
25b	You have knowledge about biodiversity. *(1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly agree)*	2.648	0.947	1	5
26a	Planting different tree species on farms has ecological consequences. *(1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly agree)*	3.6	0.701	3.6	.701
26b	You have knowledge about the ecological consequences of planting different tree species. *(1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly agree)*	2.903	0.981	1	5

Note: *n*=145.

Table 3.16: *Theory of Planned Behaviour: Intention*

	Intention	Mean	SD	Min	Max
22a	How is your intention to plant different tree species on your plots in the next three years? *(1=No intention, 2=Rather no intention, 3=Undecided, 4=Rather high intention, 5=High intention)*	4.4	0.606	3	5
22b	How likely is it that you will plant different tree species on your farm in the next three years? *(1=Very unlikely, 2=Not likely, 3=Undecided, 4=Likely, 5=Very likely)*	4.421	0.585	3	5

Note: *n*=145.

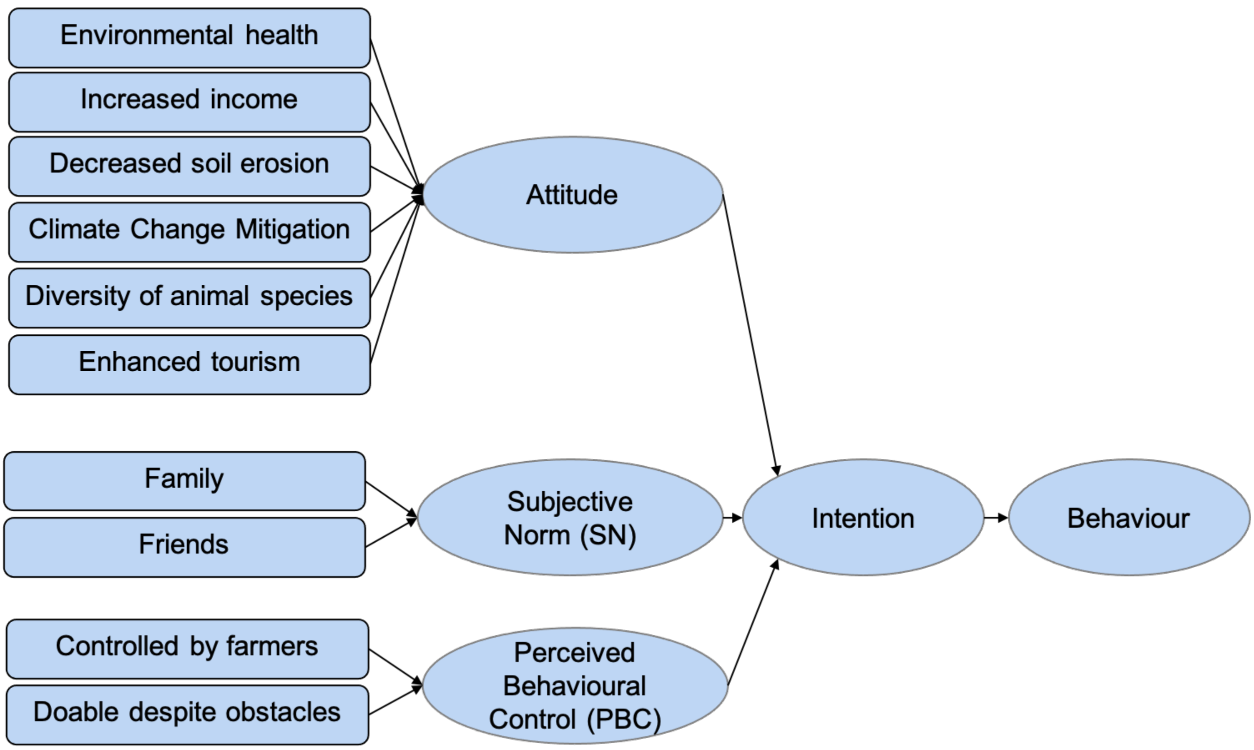

Figure 3.8: *Results of the PLS-SEM.*

Note: All weights and path coefficients of the constructs shown are significant at α=5%. Knowledge was not significantly associated with intention to adopt diversified agroforestry.

Experimental design, materials, and methods

The data originates from three study sites located in Rwanda's Western province, Karago, Jenda, and Nyundo sectors. These sectors reflect characteristics typical for agricultural systems in rural highlands of densely populated regions, where smallholder farmers operate on hillside plots and face environmental hazards such as landslides and soil erosion. From each sector, 48 or 49 small-scale farmers were randomly selected to participate in the structured household survey, comprising a total sample of 145 farmers. The face-to-face interviews were conducted in Kinyarwanda language during October and November 2020. The first part of the questionnaire contained 25 questions related to socioeconomic characteristics and farming activities. The second survey section covered the Theory of Planned Behaviour. The data collection was tablet-based using the software ODK. For data cleaning and the descriptive analysis, the responses were imported to Stata 16 [2]. The PLS-SEM was estimated using SmartPLS 3[3].

The TPB-part of the questionnaire was based on previous surveys [4-8] and adjusted to the case study area. This survey section contained 26 questions related to attitude, subjective norm, perceived behavioural control, knowledge, and intention as displayed in the tables. Each question related to the constructs which were used to predict intention (attitude, subjective norm, perceived behavioural control, and knowledge) was divided into two parts. Thereby, the two parts captured the outcome belief strength and the subjective outcome evaluation (attitude), the normative belief and the motivation to comply (subjective norm), the control belief and the perceived power over the control factor (perceived behavioural control), as well as required knowledge and personal knowledge status (knowledge). The respondents indicated their agreement with each question on a five-point Likert scale, linked to a verbal description of the scale. Both parts were multiplied to generate the respective TPB-indicator for the measurement model. Accordingly, each indicator item had a possible maximum value of 25 after multiplication [1,9,10].

The TPB-framework was operationalized via a PLS-SEM. A structural equation model poses as a multivariate statistical framework to analyze interrelationships between observable (indicator items) and latent variables (TPB-constructs) [11]. A PLS-SEM aims to maximize the proportion of explained variance of endogenous constructs. It is particularly well-suited when the sample sizes are small and the research aim is to predict latent constructs [12]. In this application, the model is reflective, meaning that the measurement of the indicator item results from the constructs. Several reliability and validity checks were performed as follows.

For constructing the measurement model, which measures the latent constructs using the indicator questions, items estimating the constructs were excluded if their weight was insignificant, their loading below 0.5, and it made sense from a theoretical point of view. To evaluate the construct validity of the measurement model, we assessed internal reliability, convergent validity, and discriminant validity. Internal reliability can be achieved when the following criteria are met: composite reliability > 0.7 and Cronbach's $\alpha > 0.7$. In view of our data, the composite reliability exceeded the specified threshold. However, the measurement model results also showed that not all latent variables had a Cronbach's α higher than 0.7, but according to Hair (2017), Cronbach's α tends to underestimate the true reliability and should therefore be regarded in conjunction with composite reliability. Taking into account the high values for composite reliability as well as the underlying theory, the respective items were kept in the model. Regarding convergent validity, we confirmed that the loadings of all items were significant. Additionally, all values for average variance extracted exceeded 0.5 for our model, hence proving convergent validity for the studied constructs. To check the extent to which the constructs differed from each other, we examined the Heterotrait-Monotrait-Ratio, cross loadings, and the Fornell-Larcker criterion, which all confirmed the measurement model's discriminant validity [12].

As a first step to evaluate the structural model, which estimated the relationships between the constructs, we assessed multicollinearity by checking the variance inflation factor, which was below 5 for all items. Next, we tested significance and relevance of the path coefficients of the constructs, which were significant and relevant except for knowledge. In addition to the direct effects, we also checked for moderation effects, but did not find any significant results. R^2 was 0.25 and thus rather weak. Assessing the influence of the individual constructs including attitude, subjective norm, and perceived behavioural control on intention showed that f^2 was highest for attitude and exceeded the threshold of 0.02 for all constructs. Generated via blindfolding, the value for Q^2 was 0.212 and thus lied above zero. This indicates that the model has predictive relevance for the endogenous construct [12].

Ethics statement

The researchers ensured that all respondents were well informed about the study's background and aim. They also confirmed the data's confidentiality. All respondents gave their informed consent to participate in the survey. The dataset was anonymized.

CRediT author statement

Beatrice Noeldeke: Conceptualization, Formal analysis, Investigation, Data curation, Writing-Original draft, Writing - Review & Editing, Visualization. **Ronja Seegers:** Conceptualization, Investigation, Visualization, Writing - Review & Editing. **Etti Winter:** Conceptualization, Project administration, Supervision, Writing - Review & Editing. **Elisée Bahati Ntawuhiganayo:** Investigation.

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Acknowledgments Declarations of interest

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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Appendix D: Further Simulation Results

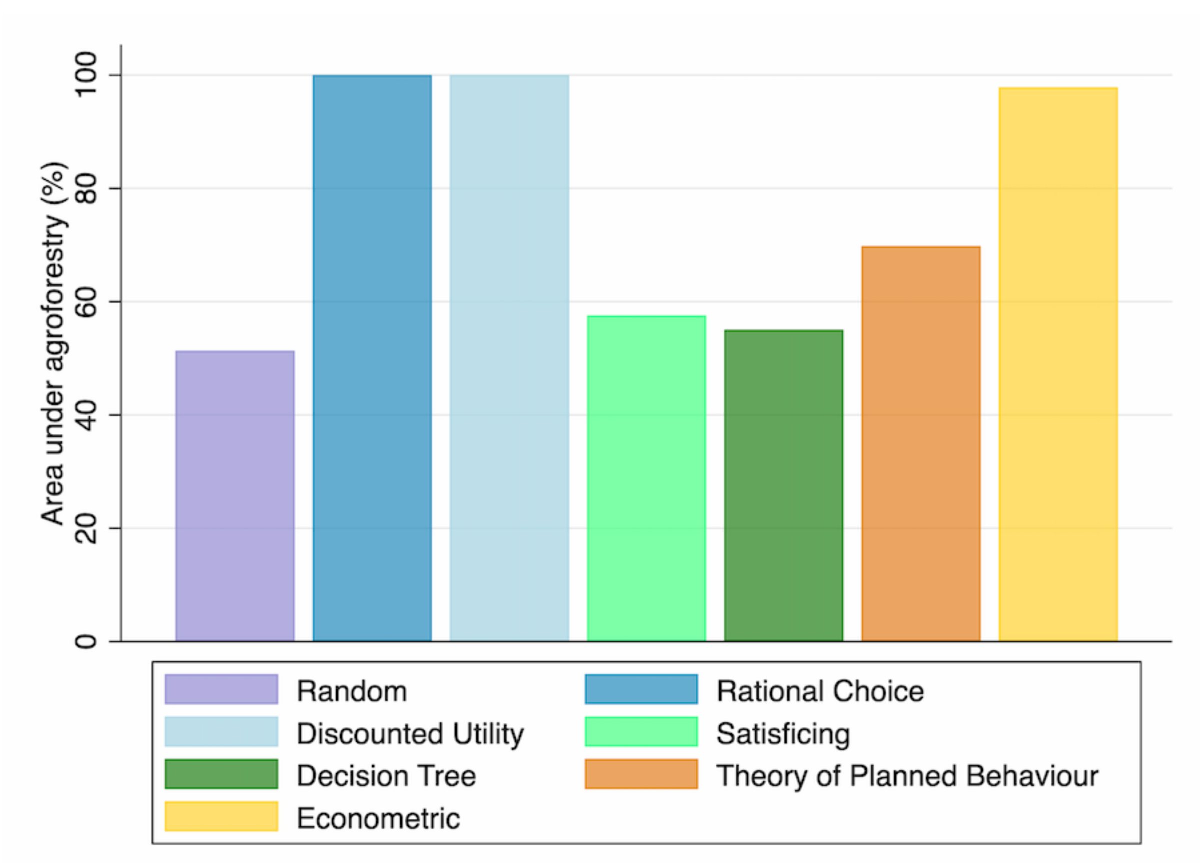

Figure 3.9: *Area under agroforestry in year 1.*

Note: Blue bars: Perfect rationality, green bars: Bounded rationality.

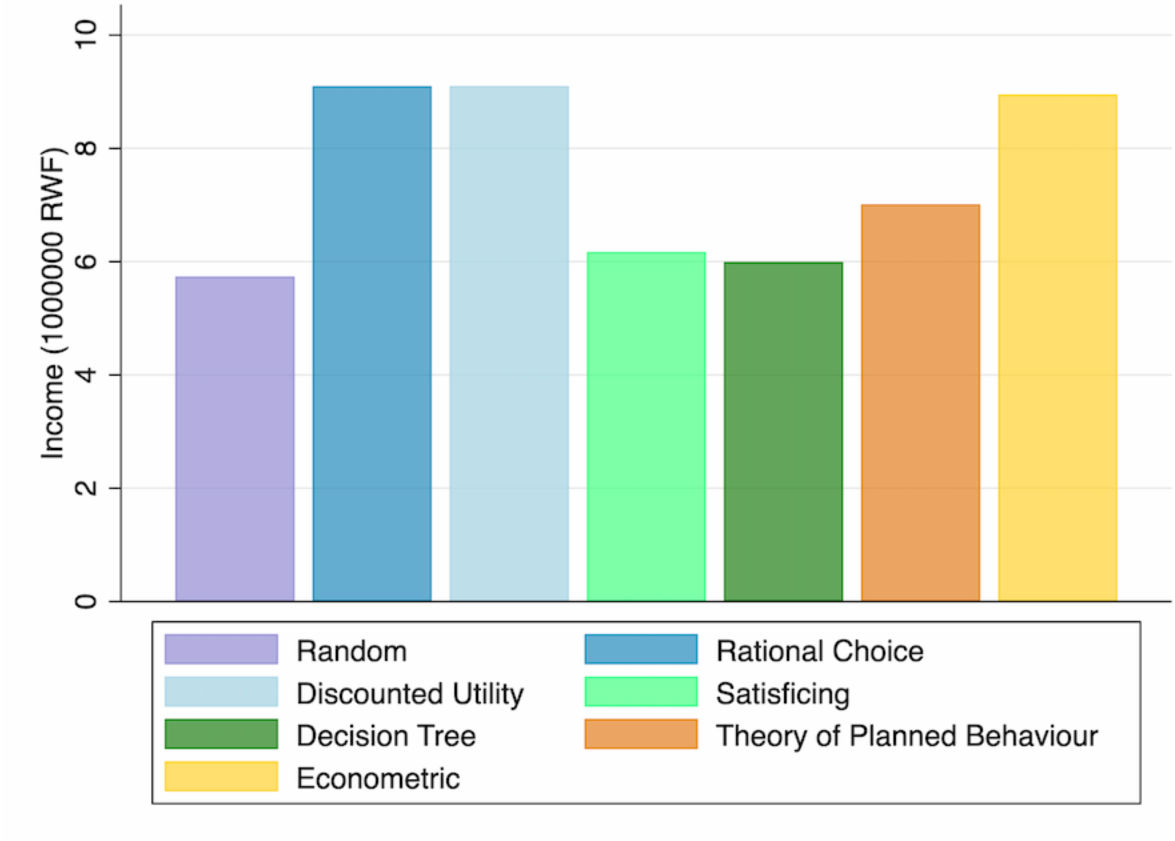

Figure 3.10: *Income in year 1.*

Note: Blue bars: Perfect rationality, green bars: Bounded rationality.

4. Promoting Agroforestry in Rwanda: the Effects of Policy Interventions Derived from the Theory of Planned Behaviour

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Sustainable Production and Consumption

Abstract

Although agroforestry offers multiple benefits, its adoption by small-scale farmers remains low in some regions in developing countries. Besides economic motives also intrinsic motivations can influence farmers' behaviour. This study identifies farmers' intrinsic drivers to adopt agroforestry based on the Theory of Planned Behaviour. Furthermore, it compares policy instruments which address the intrinsic drivers to promote agroforestry adoption. Specifically, an agent-based simulation model investigates whether the following interventions increase adoption intentions 1) an information campaign to spread awareness of agroforestry benefits to strengthen positive attitudes, 2) informing farmers about social norms to reinforce their perception of subjective norm, and 3) providing trainings to improve farmers' perceived behavioural control. The research is applied to a case study in rural Rwanda. In line with the Theory of Planned Behaviour, a partial least squares structural equation model confirms that attitude, subjective norm, and perceived behavioural control influence farmers' adoption intention. The simulations demonstrate that all interventions significantly increase farmers' intention to adopt agroforestry, but their effectiveness is rather small. The information campaign targeting attitude causes the strongest increase. The relatively weak effectiveness of the individual interventions can be enhanced by their combined implementation. Policy-makers who aim to raise low agroforestry adoption rates should consider strategies that target intrinsic drivers as alternatives to economic incentives.

Keywords: Agroforestry; Innovation Adoption; Theory of Planned Behaviour; Policy Interventions; Small-scale Farming

4.1 Introduction

Scientists as well as policy-makers frequently promote agroforestry as a sustainable agricultural practice to address climate change and food security challenges (Ndlovu and Borrass, 2021; Rosenstock et al., 2019; WBGU, 2021). Agroforestry describes the integration of trees with other agricultural activities (Abbas et al., 2017). As a sustainable agricultural practice, it can produce food and non-food outputs, improve nutrient and water cycling, contribute to soil fertilization, and enhance crop yields. At the same time, agroforestry mitigates climate change through CO_2 sequestration and conserves biodiversity (Ahirwal et al., 2022; Santos et al., 2019; Wangpakapattanawong et al., 2017; WBGU, 2021). This practice promotes food security and increases resilience. Hence, small-scale farmers in developing countries, whose livelihoods depend on agriculture and who are especially vulnerable towards climate change, can benefit from agroforestry in particular (Reppin et al., 2020; Wangpakapattanawong et al., 2017). However, the low uptake of agroforestry in certain regions, especially in parts of Africa, poses an obstacle to realize its numerous benefits (Amare et al., 2019; Do et al., 2020; Ndlovu and Borrass, 2021; Partey et al., 2017). Governmental support can remove barriers and encourage small-scale farmers' adoption (Baig et al., 2021; Iiyama et al., 2017, 2018b; Jacobi et al., 2017). Therefore, effective policy measures are needed to raise low agroforestry adoption rates (Hilbrand et al., 2017; Ndlovu and Borrass, 2021).

When developing effective policy interventions to support adoption, policy-makers need to consider the reasons for low uptake rates and thus account for factors that drive farmers' decision-making (Dessart et al., 2019; Meijer et al., 2015a). Numerous studies have established that economic reasons can motivate farmers to adopt new agricultural practices (e.g. Iiyama et al., 2018a; Oduro et al., 2018; Ren et al., 2021; Staton et al., 2022; Zulfiqar et al., 2021). However, policy interventions that are based on financial incentives may not be effective in certain cases. For example, empirical evidence suggests that the fear of damaging their reputation may prohibit farmers from adopting promoted practices (Läpple and Kelley, 2013; Sereke et al., 2016). Thus, social norms and the desire to act in accordance with other people's behaviour can impact agricultural decisions (Buyinza et al., 2020b; Chandrasekhar et al., 2018; Kremer et al., 2019; Llewellyn and Brown, 2020; World Bank, 2015). Moreover, adoption may depend on farmers' attitudes towards on-farm tree planting, which can reflect perceived risks and subjective perceptions associated with the practice (Buyinza et al., 2020a, 2020b; Jha et al., 2021; McGinty et al., 2008; Meijer et al., 2015b; Olum et al., 2020). Furthermore, farmers' opinions regarding their abilities and control over the behaviour can influence their decision

(Buyinza et al., 2020a, 2020b; McGinty et al., 2008). Complementing the empirical evidence, the Theory of Planned Behaviour (TPB) postulates that behaviour is based on a goal-directed, deliberate decision process and that behavioural intentions are formed by attitude, subjective norm (SN), and perceived behavioural control (PBC) (Ajzen, 1991). Attitude describes the extent to which a person holds a favourable or unfavourable evaluation of the respective behaviour. SN reflects the beliefs whether important reference individuals or groups approve the behaviour, and PBC describes the perceived ease or difficulty to perform the behaviour (Ajzen, 2006, 1991; Fishbein and Ajzen, 2010; Lima and Bastos, 2020). Policy-makers should consider these socio-psychological factors instead of implementing top-down supply-push approaches to develop and implement effective interventions (Dessart et al., 2019; Iiyama et al., 2018b; Jha et al., 2021; Meijer et al., 2015a).

To identify effective instruments that influence farmers' agricultural decisions, a few authors have compared different policy interventions. In the context of promoting tree planting and forest conservation among landholders, previous studies have assessed the effectiveness of financial incentives such as subsidies and payments for ecosystem services (e.g. Ruseva et al., 2015; Salvini et al., 2016; Villamor et al., 2014; West et al., 2018). Only few authors have tested behavioural, non-economic interventions to raise agroforestry adoption rates. For example, Romero et al. (2019) stated that changes in perception and intention due to an information campaign increased adoption among smallholder oil palm farmers in Indonesia. Buyinza et al. (2020b) found that farmers who participated in agroforestry projects were motivated by more positive evaluations and higher perceived capability to implement the practice, whereas social pressure was more important to farmers who did not participate in the project. The sparse literature on policy interventions based on behavioural insights in the field of agriculture reflects the limited insights on the efficiency of these instruments for behaviour change (Rose et al., 2018). Thus, more research testing different behavioural interventions is needed to investigate how effectively non-economic policy instruments promote adoption among small-scale farmers (Lourenco et al., 2016; Palm-Forster et al., 2019; Rose et al., 2018).

The purpose of this study is to identify intrinsic drivers of agroforestry adoption intentions using the TPB. Furthermore, it aims to test the effectiveness of non-economic interventions which address the identified intrinsic drivers to promote agroforestry adoption. An agent-based model (ABM) simulates three policy interventions derived from the TPB and compares their effects on small-scale farmers' intention to cultivate diverse tree species on their farms. The

simulated policy strategies include 1) an information campaign to spread awareness of agroforestry benefits to strengthen positive attitudes, 2) informing farmers about social norms to reinforce their perception of subjective norms, and 3) providing trainings to improve farmers' perceived behavioural control over planting diverse tree species. The research is applied to a case study in rural Rwanda, where agroforestry offers a promising pathway for advancing livelihoods and food security as well as combating environmental problems (Mukuralinda et al., 2016). The study contributes to the limited literature on behaviourally-informed interventions in the field of agriculture. It provides insights into how interventions derived from the TPB as alternatives to financial rewards or input provision can motivate agroforestry adoption. Thus, the study supports policy-makers in evaluating cost-effective strategies addressed at intrinsic drivers to raise agroforestry adoption rates.
The study is organized as follows. The subsequent chapter introduces the TPB. Chapter 4.3 presents the data and describes the ABM. The results are presented in chapter 4.4 and discussed in chapter 4.5. The last section summarizes and concludes.

4.2 Theory of Planned Behaviour

To account for social influences and subjective perceptions when investigating agroforestry adoption decisions, this study employs the Theory of Planned Behaviour. According to this socio-cognitive theory, behaviour is directly determined by intention. The stronger the intention to perform a certain behaviour is, the more likely its execution becomes. Intention itself is formed by three TPB-constructs: attitude, SN, and PBC, as figure 4.1 illustrates (Ajzen, 2006, 1991; Lima and Bastos, 2020). A more favourable attitude, higher SN, and greater PBC lead to a stronger intention to perform the behaviour in question.

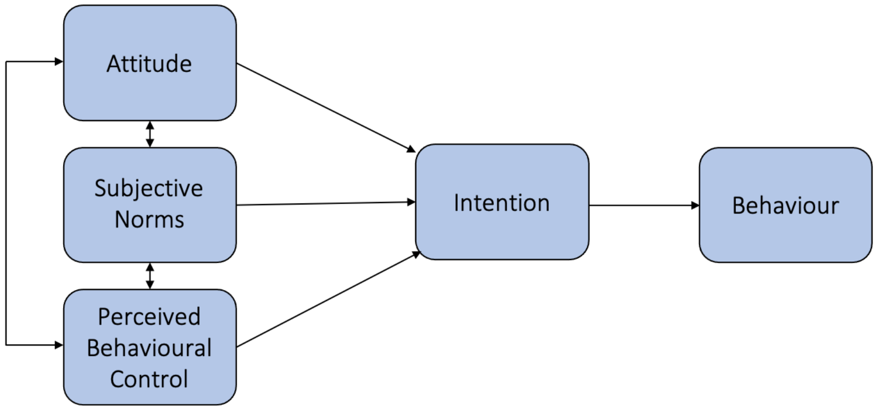

Figure 4.1: *Framework: Theory of Planned Behaviour.*

Source: Adapted from Ajzen (1991) and Fishbein and Ajzen (2010).

Attitude is formed by salient beliefs about the behaviour's likely outcomes and the subjective evaluation of these outcomes (Ajzen, 2006, 2005, 1991; Meijer et al., 2016). Attitude as a TPB-construct can be calculated as follows

$$Att = \sum_{i=1}^{I} b_i * e_i \qquad 4.1$$

b_i reflects the strength of each salient behavioural belief i, for example to what degree a farmer believes that cultivating diverse tree species on their farm increases income. e_i describes the subjective evaluation of the belief's attribute, e.g. to what extent the farmer approves increased income. The products of the behavioural beliefs and their subjective evaluation over all *I* salient beliefs are summed up to compute the construct attitude (Ajzen, 1991; Ajzen and Fishbein, 2000; Meijer et al., 2016).

SN captures the perceived social pressure to engage in or refrain from the behaviour as follows

$$SN = \sum_{i=1}^{I} n_i * m_i \qquad 4.2$$

For calculating SN, each normative belief strength regarding the respective reference group's approval (n_i) is multiplied by the individual's motivation to comply with the respective group's approval (m_i). Summing the products of all I salient reference groups yields the SN (Ajzen, 2006, 1991; Lima and Bastos, 2020).

The concept of PBC is related to an individual's self-efficacy and captures key skills, past experiences, and expected difficulties. Individuals perceive higher behavioural control if they are convinced to have the relevant resources and opportunities and anticipate few obstacles to perform the behaviour. The PBC can be expressed by summing up the products of each control belief and the perceived power over these control factors as follows:

$$PBC = \sum_{i=1}^{I} c_i * p_i \tag{4.3}$$

c_i describes the control beliefs, e.g. how likely individuals might encounter a control factor when performing the behaviour. p_i reflects the power over the respective control factor (Ajzen, 2006, 1991; Fishbein and Ajzen, 2010; Lima and Bastos, 2020).

Overall, the TPB provides a suitable framework for explaining decision-making and predicting farmers' behaviour (Buyinza et al., 2020a; Groeneveld et al., 2017; Hine et al., 2015; Maleksaeidi and Keshavarz, 2019). Researchers have applied the TPB to explain farmers' pro-environmental behaviour, including agroforestry adoption (Buyinza et al., 2020a, 2020b; McGinty et al., 2008; Meijer et al., 2016, 2015b; Sereke et al., 2016; Sood and Mitchell, 2004), related management practices (Cahyono et al., 2020), farm forestry (Zubair and Garforth, 2006), and on-farm biodiversity conservation (Zeweld et al., 2017).

4.3 Data and Methodology

Study area

This study is applied to a case study in rural Rwanda. Rwanda is a land-locked country located in the central African highlands occupying an area of only 26.338 km^2 (Bagstad et al., 2020; FAPDA, 2016). A mountainous relief characterizes this country, whose altitude ranges from 900 m to 4500 m. Rwanda has a tropical climate with abundant rainfalls and mean annual temperatures ranging from 16°C to 20°C (European Commission and Republic of Rwanda, 2006). With over 11 million inhabitants, Rwanda is the most densely populated country in Africa (FAPDA, 2016). This population largely depends on rain-fed agriculture for their livelihoods. Thus, agriculture is the main land use and contributes to almost 90% of total employment (FAPDA, 2016; Nishimwe et al., 2020). Most farmers cultivate plots smaller than one hectare, as the high population density makes land a scarce resource in this country (Iiyama et al., 2018a; Nishimwe et al., 2020). During the last decades, natural forests and woodland were converted into arable land, resulting in a severe loss of ecosystem services (Bagstad et al., 2020). As a result, Rwanda's agricultural sector faces major environmental challenges including biodiversity loss, land degradation, and reduced productivity (Iiyama et al., 2018a; Paul et al., 2018). Additionally, farmers in rural areas face high risks for soil erosion as most of their plots are located on slopes (Bagstad et al., 2020; Republic of Rwanda and Ministry of Agriculture and Animal Resources, 2020). Thus, agroforestry offers a promising solution to address these challenges and provide benefits to farmers and the environment (Iiyama et al., 2018a).

Data collection

This study focused on three study sites located in Rwanda's Western Province: Karago, Jenda, and Nyundo sector, as figure 4.2 visualizes. These sectors reflect typical characteristics of agricultural systems implemented in rural highlands of densely populated areas, where farmers operate on small hillside plots and are exposed to environmental hazards such as landslides and soil erosion. In this study area, a structured survey was conducted. The first part of the questionnaire covered socioeconomic characteristics and farming activities. The second survey section consisted of indicators to estimate the TPB-constructs. These TPB-indicators captured the behavioural beliefs and their subjective evaluation (attitude), normative beliefs and the associated motivation to comply (SN), as well as control beliefs and the perceived power over these control factors (PBC) based on a five-point Likert scale. The sample comprised a total of 145 randomly selected small-scale farmers, who were interviewed in October and November 2020.

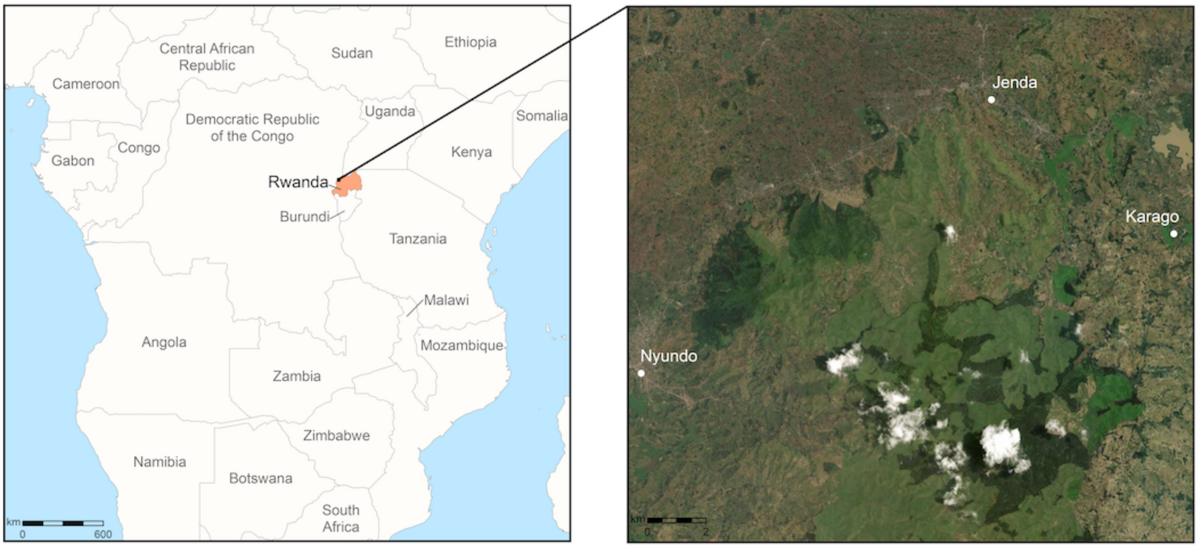

Figure 4.2: *Study area*

Data analysis

The survey data were cleaned and analysed descriptively in Stata 16 (StataCorp, 2019). A partial least squares structural equation model (PLS-SEM) approach based on the software SmartPLS 3 was used to operationalize the TPB-framework and estimate the relationships between the latent TPB-constructs and the observable TPB-indicator items for identifying relevant intrinsic drivers (Ringle et al., 2015; Stein et al., 2012). This multivariate model maximizes the explained variance of the endogenous latent variables. One advantage of this approach is its ability to enable forecasts (Hair et al., 2017). These descriptive and econometric results formed the basis for the developed agent-based simulation model, which the next section describes in detail. Analysis of Variance (ANOVA) was used to compare the simulated policy scenarios using Stata 16.

Agent-based Model

Agent-based simulation models offer an advantageous tool to analyse the effectiveness of policy interventions: by providing a virtual context-specific laboratory, they can examine alternative policy options in an ethical, time-, and cost-effective way (Ahrweiler, 2017; Gilbert et al., 2018). The implemented ABM is based on the Biodiversity and Adoption of Small-scale Agroforestry in Rwanda (BASAR) model (Noeldeke et al., 2022). The following presentation of the implemented model is based on the Overview, Design Concepts and Details + Decision-making (ODD+D) protocol (Grimm et al., 2020, 2010, 2006; Müller et al., 2013). Sections that are identical to the previous model version are not presented here, but they can be found at https://www.comses.net/codebase-release/55065bfb-08ec-4a15-9357-82797a82e7f0/. The ODD+D protocol refers to the baseline scenario without any interventions. The policy scenarios are introduced subsequent to the model description.

1) Overview:

I.i Purpose: The model examines how effectively different policy interventions targeting intrinsic drivers derived from the TPB motivate Rwandan small-scale farmers to adopt agroforestry systems with diverse tree species as an alternative to potatoes and wheat rotations. It is addressed at policy-makers in the early stages of policy development. The model aims to shed light on the suitability of different non-economic policy instruments to raise low adoption rates and thus to support policy design.

I.ii Entities, state variables, and scales: The main model entities are the agents representing small-scale farming households. These farming households decide whether to implement agroforestry systems on their farms. They are characterized by variables describing their labour force, land size, number of friends, and TPB-indicators. Table 4.1 in the Appendix contains further details regarding the household agents' attributes. Households can be connected with each other via links. Through these links households can exchange information about the adoption of agricultural practices. The model's spatial landscape is described by plot agents. They represent the land owned by the farming households. The household agents' behaviour determines their land cover. Table 4.2 in the Appendix provides an overview over the plot agent variables. The model includes space explicitly, based on approximated land sizes calculated from the survey data. Each square grid cell represents 0.5 ha, and the model landscape represents 60 x 60 ha. One time step represents one year.

I.iii Process overview and scheduling: During every time step simulated, the following procedures take place in the order presented in figure 4.3. First, the plot agents representing the agricultural ecosystem execute the vegetation transition. Subsequently, the farming agents carry out the information exchange submodel, during which they can receive information about agroforestry. The households that know about the agricultural practice decide whether to implement agroforestry or continue to grow traditional crops. Next, farming households may harvest produced agricultural outputs depending on their land use. Farmers who adopted agroforestry on their plots must maintain the trees in certain years. Surplus family labour that was not needed for the household's farming activities is used to generate additional income. Finally, outputs are updated. Once a household has adopted agroforestry, this land use is retained for 20 years until the trees mature, and only then can households re-evaluate their decision whether to adopt agroforestry again or return to traditional crop rotations. During each procedure, the order of agents performing the respective procedure is random. The model simulates time periods of 30 years, which is sufficiently long to cover the duration until timber can be harvested from the agroforests.

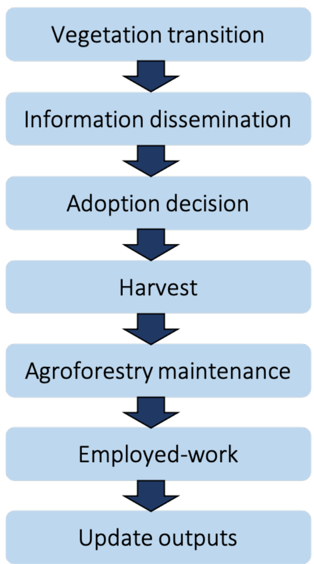

Figure 4.3: *Agent-based model: process overview*

II) Design concepts

II.i Theoretical and empirical background: The modified version of the BASAR model simulates farmers' decision to adopt agroforestry based on the TPB. It compares different policy interventions aimed at strengthening farmers' intention to plant diverse tree species on their farms. Land use and land cover emerge from household-level decisions. Household survey data from rural Rwanda provides the empirical basis for the model.

II.ii Individual decision-making: The farming households who have not implemented agroforestry decide about adopting this sustainable agricultural practice based on the TPB. Thus, the model includes farmers' objectives implicitly. The households compute their individual attitude, SN, and PBC based on the PLS-SEM results using the TPB-indicators from the survey. They calculate their intention as follows:

$$Intention_i = w_{Att} * Att_i + w_{SN} * SN_i + w_{PBC} * PBC_i \qquad 4.4$$

with the weights $w_{Att} = 0.43$, $w_{SN} = 0.18$, and $w_{PBC} = 0.13$ in line with the PLS-SEM results. Whereas the effects of attitude and PBC on intention remain constant, the influence of SN increases over time if the household is exposed to a large share of adopters in their network. The computed value for intention is rescaled to match the model's time scale and to fall in the interval between 1 and 100 so that it can be interpreted as the adoption probability.

II.iii Individual sensing: The households are aware of their own state variables and their plots' current land cover. Additionally, they know quantities and prices of agricultural inputs and outputs. They are also aware of who in their social network has adopted the agroforestry system.

II.iv Interaction: Farmers share information regarding the agricultural practice and who has already adopted it through their social networks. Thereby, a high proportion of adopters in the network reinforces the perception of the SN to adopt.

II.v Heterogeneity: The farming households differ in terms of their state variables according to the survey. As the items used to calculate attitude, SN, and PBC are also parameterized based on the survey, farmers are heterogeneous in their intrinsic drivers and adoptions.

II.vi Stochasticity: The initialization procedure comprises stochastic elements such as random household and farm locations and establishment of connections with randomly selected households. The information dissemination procedure contains randomness as farmers receive information from an external information source or through their social network with a certain probability. Farmers' intention is implemented as an adoption probability. Furthermore, farmers receive the policy intervention with a certain likelihood.

II.vii Observation: The main model outcome is the mean adoption intention. Further outputs include land use and the proportion of households aware of the agricultural practice. The rate of households aware of the agricultural practice is computed monthly, while the other outcomes are reported annually.

III) Details

III.i Implementation details: The model was implemented in NetLogo 6.2.1 (Wilensky, 1999). The model code is available at https://www.comses.net/codebase-release/b6be1774-519e-40b4-96f0-70ff9e2f7405/.

III.ii Initialization: The model is initialised with 145 randomly located agents representing farming households in the case study area. Their state variables are parameterized according to the survey. A Watts-Strogatz network is established based on the reported number of contacts with whom the farmers discuss agricultural issues. Such a network exhibits characteristics of a small-world network such as relatively high clustering and short average distances (Borgatti et al., 2018). Based on the land size reported in the survey, the closest landscape patches are assigned to the households as their plots. Initially, all farmers cultivate potatoes and wheat crops on their plots. Finally, global variables such as prices, outputs, and parameters related to the TPB decision-making module are set up.

III.iii Submodels: Because the vegetation transition, harvest, agroforestry maintenance, and update outputs modules are identical to the original BASAR model version, the following section describes only the adjusted modules. The modified adoption decision is described in section II.ii Individual decision-making.

Information dissemination: Being aware of an innovative agricultural practice is a necessary prerequisite for adoption. Households that have access to official information sources, such as media, extension services, or their village heads, can obtain information about the agroforestry system with a certain probability. Information initially enters the community via these official information sources, but farmers may receive knowledge about agroforestry also through their social network: if households have obtained information, they share it with other households in their network with a certain likelihood. Whereas the other procedures are carried out annually, information dissemination takes place monthly.

Employed work: Households can use surplus household labour, which was not needed for their own agricultural activities, to generate additional income outside the household.

Policy intervention scenarios

The described baseline scenario is compared to three policy intervention scenarios. The first policy intervention scenario simulates an information campaign that targets farmers' attitudes. The campaign promotes benefits of planting different trees species on farms, such as increased incomes, timber availability, increased tourism, enhanced animal species diversity, and climate change mitigation. The intervention is assumed to improve farmers' behavioural beliefs. The second simulated policy measure targets SN. By spreading messages informing about social norms, this instrument aims at increasing the perceived social pressure on farmers to adopt agroforestry. This policy tool is assumed to reinforce normative beliefs by disseminating information about injunctive norms, e.g. that farmers' friends and family support agroforestry adoption, through the media or personalized messages. The third policy intervention involves trainings on on-farm tree cultivation targeting PBC. It is assumed to increase farmers' perceived power over control factors by improving their confidence in adopting agroforestry. The interventions are implemented during the whole simulation period. Randomly targeted farmers receive the interventions with a probability of 50% every year. The policy instruments are assumed to affect farmers' TPB-indicators related to behavioural beliefs, normative beliefs, or perceived power. Specifically, the interventions are assumed to result in a two-unit increase on the five-point Likert scale for the respective TPB-indicators, up to a maximum score of five (medium impact). A sensitivity analysis tests an increase of one (low impact) and three points on the Likert scale (high impact). The simulations were repeated 50 times for each scenario.

4.4 Results

Intrinsic determinants of agroforestry adoption intentions

This study identifies intrinsic drivers of agroforestry adoption decisions based on the TPB. A PLS-SEM is used to estimate the relationships among the TPB-constructs and farmers' intentions. According to PLS-SEM results, farmers' attitude, SN, and PBC significantly impact their adoption intentions, as figure 4.4 illustrates. Among the constructs, attitude has the largest effect with a path coefficient of 0.425 (p=0.000). This indicates that attitude is the main determinant of farmers' intention to cultivate diverse tree species on their farms. SN has a considerable, yet smaller, influence on intention, as the path coefficient of 0.182 reflects (p=0.036). PBC exerts the lowest effect with a path coefficient of 0.131 (p=0.045).

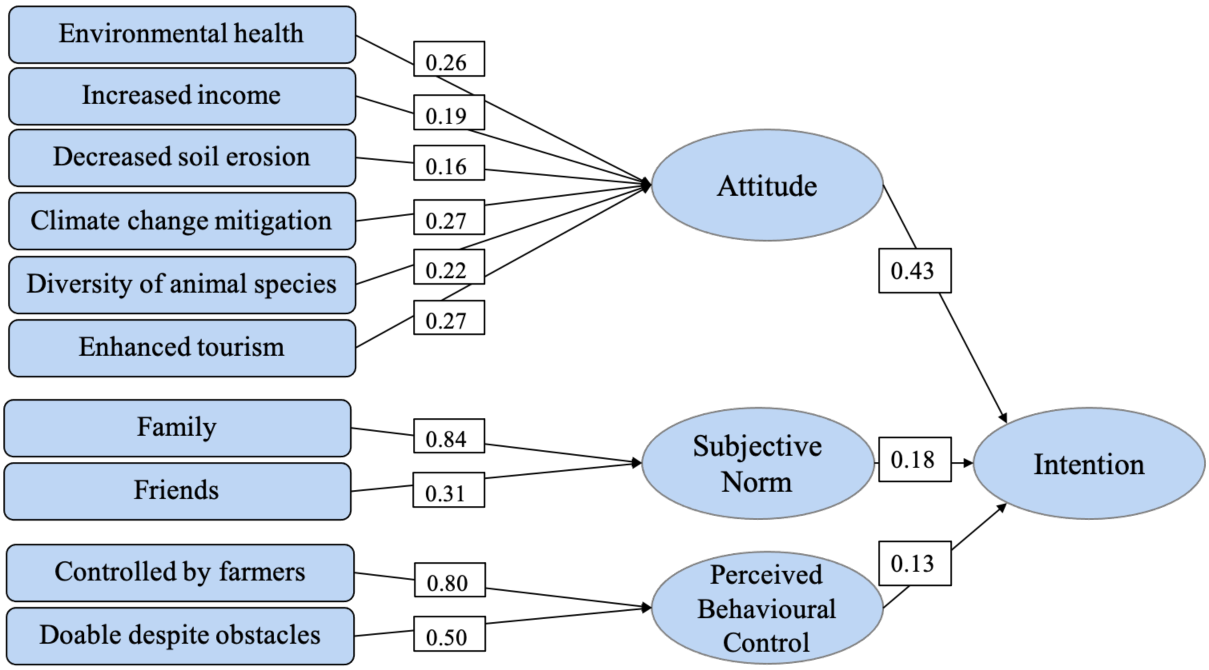

Figure 4.4: *Results of the PLS-SEM.*

Note: R^2*=0.25.* Q^2*=0.212. Weights and path coefficients of all shown indicators and constructs are significant at* α*=5%.*

Based on the survey results, the PLS-SEM provides further details into the TPB-constructs and how they are formed. The survey responses suggest that the farmers hold generally positive attitudes towards agroforestry as they associate positive outcomes with its implementation and also value these beneficial outcomes. The factor analysis based on the survey results shows that out of the tested indicators the following aspects significantly shape farmers' attitude: income, tourism, environmental health, climate change mitigation, soil erosion protection, and animal diversity. Furthermore, most respondents believe that other people are in favour of planting diverse tree species, and farmers want to adhere to this perceived injunctive norm according to the survey. The PLS-SEM shows that family and friends constitute the significant reference groups. Consequently, the estimated SN also tends to be strong. The farmers generally believe that certain control factors are important for planting diverse trees species, and they have confidence in their abilities to control these factors. Specifically, most respondents express that they themselves control planting different tree species and that they personally feel confident to exert this control. Moreover, most farmers agree that planting different tree species is feasible despite potential obstacles, such as extreme weather events, lack of institutional support, insufficient knowledge, lack of land, and unavailability of seedlings, and that they can personally overcome these obstacles, according to the survey and the PLS-SEM results. Therefore, farmers' estimated PBC also tends to be high.

The measurement model's construct validity is evaluated as follows: composite reliability and Cronbach's α assess internal reliability, loading significances and average variance extracted confirm convergent validity, and the Heterotrait-Monotrait-Ratio, Cross loadings, and the Fornell-Larcker criterion attest discriminant validity. Evaluating the structural model includes assessing multicollinearity using the variance inflation factor and checking significance and relevance of the constructs' path coefficients as well as R^2, f^2, and Q^2 (Hair et al., 2017). Evaluating the model's goodness-of-fit shows that the tested values are within the recommended ranges or support the underlying theoretical framework. Overall, this confirms that the model is significant.

Policy interventions addressing intrinsic drivers increase adoption intentions

To evaluate the impact of policy interventions derived from the TPB, an agent-based model simulates their effects on farmers' intention to adopt agroforestry. The results demonstrate that the interventions targeting attitude, SN, or PBC all increase farmers' adoption intention, as figure 4.5 illustrates. The ANOVA confirms that the policy instruments lead to significantly different intention levels (p=0.000, DF=3, F=343.25), with significant differences between all interventions compared to the baseline scenario without any intervention. However, the effects on intention are rather small. The intervention targeting attitude has the largest effect among the policy measures and improves intention by 3 percentage points (p.p.). The interventions targeting SN and PBC each increase intention by just 1 p.p. Combining policy measures to target all three TPB-constructs at the same time improves intention by as much as 5 p.p. (p=0.000, DF=7, F=712.99). Thereby, intention rises most if all three interventions are implemented simultaneously, followed by combining the attitude-intervention with targeting either PBC or SN, as figure 4.7 in the Appendix visualizes.

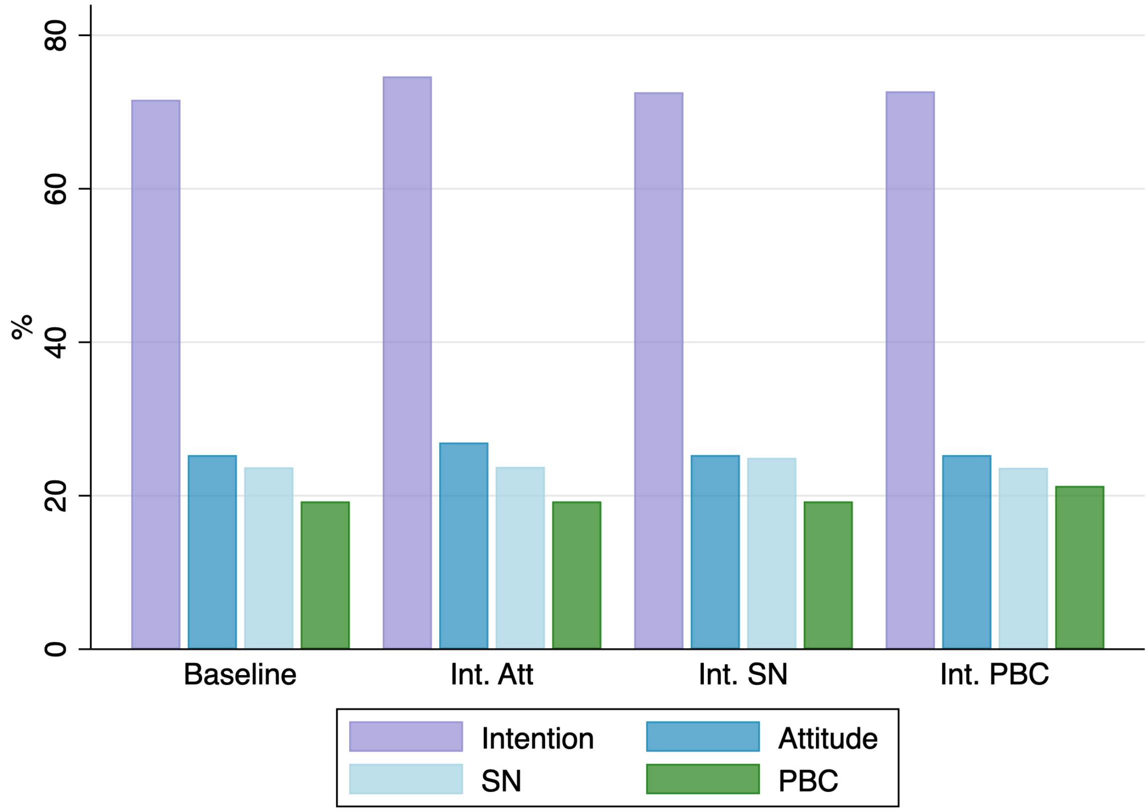

Figure 4.5: *Simulation results: intervention effects*

The simulation results further show that in all scenarios intention significantly increases over time (p=0.000, DF=2, F=152.45). This effect is due to the SN: when farmers are exposed to more adopters in their social network, the perceived SN intensifies and consequently increases intention. However, also this effect is rather small with an average intention increase of 1.5 p.p. over the first five years, as figure 4.6 summarizes.

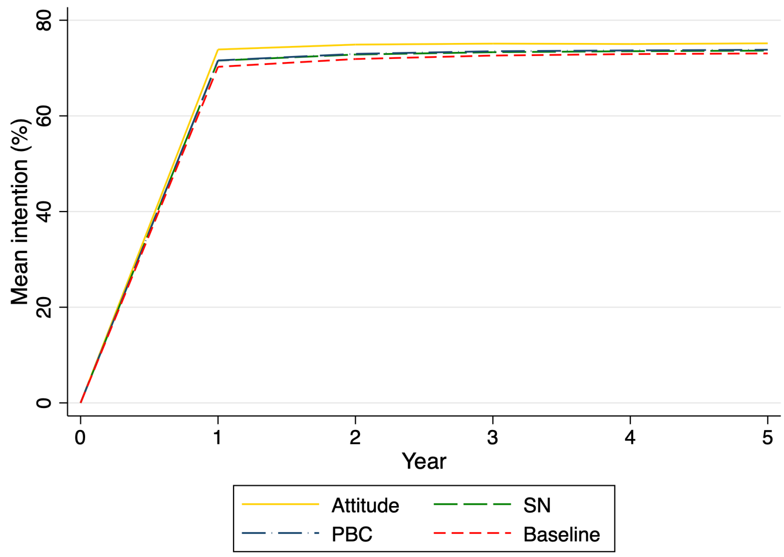

Figure 4.6: *Simulation results: mean intention over the first five years*

A sensitivity analysis modifies several intervention parameters to assess the robustness of the results. One change concerns strength of the policy effect on the TPB-indicators. This policy effect is reflected by the assumed increase of the TPB-indicators' Likert scale scores in response to the interventions. According to the simulations, the strength of the intervention effect on the TPB-indicators significantly affects intention, but the differences are less than 1% (p=0.0132, DF=2, F=4.34). Specifically, intention levels increase significantly when the effect strength rises from low to medium (p=0.041) or high (p=0.026). In contrast, increasing the TPB-indicator effect strength from medium to high does not significantly alter intention (p=1.000). Regardless of the effect strength, targeting attitude still provides the most effective instrument. Further parameter alterations show that implementing the intervention for shorter periods of time slightly, yet significantly, decreases intention (p=0.000, DF=3, F=37.81). Moreover, intention to cultivate diverse trees improves significantly as the likelihood of receiving the intervention increases (p=0.000, DF=8, F=136.98). However, this probability needs to rise by at least 10 p.p. to affect intention at the 5% level generally.

Whereas the previously described interventions target all TPB-indicators that form the respective TPB-construct simultaneously, measures addressing only specific beliefs also significantly increase farmers' intention (p=0.000, DF=6, F=16.36). In particular, significant impacts are obtained when interventions target behavioural beliefs related to animal species diversity (p=0.0009), climate change mitigation (p=0.000), environmental health (p=0.000), income (p=0.001), or tourism (p=0.000). However, the effects are very small (below 1 p.p.) Similarly, interventions focusing on just one specific reference group to increase normative beliefs have a very small (below 1 p.p.), yet significant, impact (p=0.000, DF=2, F=29.21). Also, interventions that target single PBC-indicators significantly improve intention, with effects below 1 p.p. (p=0.000, DF=2, F=24.03).

4.5 Discussion

Farmers' intentions are intrinsically motivated

This study applies the TPB to explain farmers' agroforestry adoption decisions. The PLS-SEM results indicate that attitude, SN, and PBC significantly influence farmers' adoption intentions. These findings confirm previous results that these three TPB-constructs impact farmers' decisions to cultivate and maintain trees on their farms (Buyinza et al., 2020a, 2020b; McGinty et al., 2008; Meijer et al., 2015b) and to diversify their agricultural production (Senger et al., 2017). Similarly, attitude and SN are important determinants also for on-farm biodiversity conservation (Maleksaeidi and Keshavarz, 2019). Consistent with other studies, attitude is the strongest predictor of intention in this application (Buyinza et al., 2020a; Fife-Schaw et al., 2007). Overall, the results underpin the suitability of the TPB to explain land use decisions where farmers act under the influence of social norms (Buyinza et al., 2020a; Groeneveld et al., 2017; Hine et al., 2015; Maleksaeidi and Keshavarz, 2019) and that the related intrinsic factors have high potential to explain farmers' decision to adopt agroforestry in Rwanda.

The PLS-SEM shows that farmers' attitudes are shaped by their beliefs regarding income generation but also climate change mitigation, environmental health, and soil erosion protection among others. These findings suggest that farmers do not behave as perfect rational profit maximisers. Instead, they also consider non-economic aspects in their adoption decision. Thus, these results corroborate previous findings that income motivates farmers to implement agroforestry (Mukuralinda et al., 2016; Ndayambaje et al., 2012; Oduro et al., 2018), but that their perceptions of ecosystem services are also important drivers (Djalilov et al., 2016; Mukuralinda et al., 2016). The identification of further motivational factors such as conserving animal species diversity expands previous findings. The result that income is only one of several factors motivating farmers to adopt has important implications as it suggests that financial incentives such as subsidies may not suffice to increase agroforestry uptake (Castro et al., 2020; McGinty et al., 2008). Because social and psychological factors motivate adoption as well, they should be incorporated into policy design (Dessart et al., 2019; Sereke et al., 2016;

World Bank, 2015; Zubair and Garforth, 2006). Consequently, the TPB provides a helpful framework to identify entry points for changing farmers' motivations by targeting the internal antecedents of adoption intentions (Hardeman et al., 2002; Steinmetz et al., 2016).

Policy interventions derived from the TPB have potential to improve agroforestry adoption intentions

This study compares three interventions which are based on the TPB and aim at increasing farmers' intention to adopt agroforestry. The agent-based simulations reveal that the different interventions significantly increase intention. Consistent with other studies, these results confirm that changing social-psychological beliefs can change behavioural intentions (Ajzen, 2006; Fife-Schaw et al., 2007; Granco et al., 2019; Sheeran et al., 2016). Moreover, the findings support the proposition that financial incentives and input provision alone do not suffice to increase farmers' agroforestry adoption and should be complemented by non-economic measures.

Among the simulated scenarios, the information campaign targeting attitude has the largest effect on intention. This finding corroborates the frequently derived policy recommendation that calls to increase awareness regarding the advantages of on-farm tree planting and biodiversity conservation (Buyinza et al., 2020a; Djalilov et al., 2016; Jha et al., 2021; Lima and Bastos, 2020; Zubair and Garforth, 2006). Specifying previous recommendations, the present results indicate which benefits should be emphasized: policy-makers should promote agroforestry as a pathway to mitigate climate change, improve environmental health, conserve animal species diversity, increase tourism, and generate additional income. Thereby, policy-makers can expect the greatest impact on attitudes and intention if they promote all these beneficial outcomes simultaneously. Overall, the simulation results indicate the promising potential of information campaigns to reinforce positive attitudes and reverse negative attitudes.

The simulations reveal that also interventions targeting SN enhance farmers' intention. These results are consistent with previous studies showing that information about other farmers' behaviour can encourage farmers to save water or maintain environmental service provision after contracts end (Chabé-Ferret et al., 2019; Kuhfuss et al., 2016). For these studies, researchers spread messages containing descriptive norms, e.g. what other people typically do. In contrast, the norm investigated here is injunctive and thus refers to what farmers think others expect from them (Cialdini et al., 1990; Dessart et al., 2019). In a study investigating social nudges to improve tax compliance, messages containing injunctive norms had a smaller impact on payment likelihood than messages containing descriptive norms (Hallsworth et al., 2017). Also in the context of agroforestry adoption, injunctive norm messages have rather small effects, as the simulations demonstrate. In general, the findings are consistent with numerous authors who report that the social context, particularly social pressures, influences farmers' behaviour (e.g. Borges et al., 2014; Defrancesco et al., 2008; Martínez-García et al., 2013; Matuschke and Qaim, 2009; Mekonnen et al., 2018). This is because farmers may seek approval from their reference groups or want to show their commitment to values shared by these people (Martínez-García et al., 2013). Social norms can be vital for agricultural decisions because they may prevent farmers from adopting despite a positive attitude (Burton, 2004; Buyinza et al., 2020b; Sereke et al., 2016), but may encourage farmers, even if they hold a negative attitude (Borges et al., 2014). To harness the full potential of social norm messaging, policy-makers should identify relevant stakeholders that shape the norm (Dessart et al., 2019). In the case study, family and friends constitute the SN. This confirms other studies which report that farmers were mostly influenced by people close to them, including family, friends, and neighbours (Borges et al., 2014; Martínez-García et al., 2013). Overall, despite the small effects, the results support that informing about social norms has potential as a behavioural nudge to increase adoption among small-scale farmers.

The simulations further indicate that interventions targeting PBC improves intention. In this application, PBC captures farmers' confidence to control planting different tree species and to adopt agroforestry despite possible obstacles including extreme weather events, lack of institutional support, insufficient knowledge, lack of land, and seedling unavailability. This is consistent with findings from Uganda, where farmers' PBC was based on their ability to overcome economic barriers as well as their access to resources and required knowledge related to tree planting and management (Buyinza et al., 2020a). Several authors report that the lack of resources, such as seedlings and knowledge, is a common barrier to farmers' cultivation of on-farm trees (Djalilov et al., 2016; Mukuralinda et al., 2016; Oduro et al., 2018). The result that improving PBC can enhance farmers' intention is therefore consistent with other authors who state that trainings, for example, can encourage adoption (Coulibaly et al., 2017; Iiyama et al., 2017; Zulfiqar et al., 2021). Overall, the results underpin that reinforcing farmers' confidence to overcome possible barriers through trainings provides a promising policy instrument to increase adoption intention, but the impact might be small.

Despite their significance, the simulations reveal rather small intervention effects. Also Fife-Schaw et al. (2007) conclude that small improvements in attitude lead to negligible behavioural changes only and that modest changes in the probability of performing a behaviour require large changes in the TPB-constructs (Fife-Schaw et al., 2007). The rather small intervention effects in the case study are likely to be attributed to the fact that even without any intervention farmers report strong behavioural and normative beliefs as well as high perceived power. Positive behavioural beliefs and perceived power may origin from prior experience with agroforestry, for example through previous projects, extension services, media, or own implementation, which many farmers report in the survey. Furthermore, a lot of farmers report problems such as poor soil quality and increased occurrence of flooding and landslides due to extreme weather events. They may be aware that agroforestry can provide a solution to these challenges and consequently hold positive beliefs. Additionally, the high levels of PBC suggest that input availability is not a major barrier to most farmers, which also highlights that input provision may only have limited effects on adoption behaviour.

The results indicate that combining interventions and targeting several TPB-constructs at the same time enhances their effectiveness. Implementing several policy measures simultaneously can have a bigger impact than a single one due to additive effects (Ajzen, 1991; Chatzisarantis and Hagger, 2005; Fife-Schaw et al., 2007; Hagger et al., 2002). According to the simulations, combining the information campaign promoting agroforestry benefits with additional interventions appears especially promising. This is in line with other authors who suggest to link information provision with other behavioural interventions or material incentives such as financial rewards or inputs (Hendrie et al., 2017; Meijer et al., 2015b; Romero et al., 2019; Taghikhah et al., 2020).

Robustness tests

Confirming the findings' robustness comprised two parts. First, additional to the intervention scenarios as presented above, a sensitivity analysis investigated how changes in the model's parameters affected simulation results. The main findings were robust to changes in the social network's setup. The results were also robust to errors in the PLS-SEM estimation, as shown by changing the TPB-constructs' path coefficients and TPB-indicator weights to randomly deviate from their estimated values up to 20%. Whereas the presented simulations targeted behavioural and normative beliefs as well as perceived power over control factors, targeting the respective subjective evaluations, motivation to comply, and control beliefs instead delivered results consistent with the previous findings. Second, the non-parametric Kruskal-Wallis test confirmed the ANOVA results.

Limitations and future research

Several limitations should be noted. This study focuses on behavioural intentions rather than agroforestry implementation because observations of the actual behaviour were not available. However, an intention does not directly translate into action if farmers are incapable to engage in the behaviour (Fife-Schaw et al., 2007; Steinmetz et al., 2016). Hence, if PBC does not coincide with actual behavioural control, the model is likely to overestimate adoption. Yet, PBC can serve as a proxy for actual control if farmers can realistically judge the behaviour's difficulty (Ajzen and Fishbein, 2000). Furthermore, the simulations did not directly address the feasibility of changing behaviour through policy measures. Instead, the simulations aimed to evaluate a "what if" scenario that investigates the suitability of successful interventions based on the TPB. Although the model is empirically based and the decision-module has been validated, the impacts of the different policy interventions on farmers' actual attitudes, SN, PBC, and intention are only assessed in the context of the sensitivity analysis, but they are not verified against empirical observations due to data unavailability. Thereby, it is assumed that farmers exhibit homogenous responses due to the interventions.

These limitations can stimulate further research. Future work could expand the ABM to examine farmers' heterogenous reactions to policy interventions. Another extension could relax the assumption that each intervention only affects one TPB-construct by including spill-over effects in the model. For example, farmers might discuss an information campaign and thereby reveal a social norm. Furthermore, policy interventions could introduce novel beliefs instead of altering existing ones (Ajzen, 2006). Experimental studies could empirically test the impact of the different interventions on the three TPB-constructs. Further research could validate and test the TPB-interventions in other contexts. Moreover, policy-makers should test how farmers react to interventions that combine economic and non-economic incentives and investigate associated crowding effects.

4.6 Summary and Conclusions

Although agroforestry systems offer numerous benefits for farmers and the environment, their uptake among small-scale farmers in certain regions of Sub-Saharan Africa is low. Because financial incentives can be limited to increase adoption rates, policy interventions targeting intrinsic drivers might provide effective and cost-efficient alternatives to motivate implementation. This study investigates intrinsic motivational factors of farmers' agroforestry implementation decisions and how effectively policy interventions addressing these intrinsic drivers improve adoption intentions. A PLS-SEM identifies intrinsic adoption drivers based on the TPB. An ABM, which was applied to a case study in rural Rwanda, simulates the following interventions: 1) an information campaign to spread awareness of agroforestry benefits to strengthen positive attitudes, 2) informing farmers about social norms to reinforce their perception of SN, and 3) providing trainings to improve farmers' PBC. The findings demonstrate that attitude, SN, and PBC motivate farmers to plant diverse tree species on their farms. Furthermore, interventions that target these intrinsic drivers significantly increase farmers' intention to adopt agroforestry. The information campaign to strengthen positive attitudes shows the greatest potential to enhance intention. Spreading social norms to intensify normative beliefs and training provision to improve farmers' perceived control also significantly increase intention, but the effects are small. The interventions gain effectiveness when they are combined.

These findings can support policy-makers during intervention development by identifying promising and cost-effective complements or alternatives to financial incentives that motivate farmers to adopt agroforestry. Policy-makers should promote agroforestry benefits, in particular its potential to mitigate climate change, improve environmental health, increase tourism, and conserve animal species diversity. Furthermore, they should distribute messages about social norms held by farmers' family and friends related to agroforestry adoption. Policy-makers should also provide trainings to strengthen farmers' confidence in overcoming possible barriers and in their ability to cultivate diverse tree species on their farms. Overall, the findings underpin the importance of intrinsic aspects as motivational factors for agroforestry adoption as well as the promising, yet small, impacts of policy interventions targeting attitude, SN, and PBC.

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Appendix

Table 4.1: *Farming household variables*

Variable	Definition	Scale
Household ID	Household identification	Metric
Land size[a]	Land size claimed by household	Metric, in hectare
Plots	Set of plots claimed by household	Agentset
Household size[a]	Household size	Metric, in persons
Labour force[a]	Labour force based on working household members	Metric, in work-days per year
Initial labour force[a]	Initial labour force, auxiliary variable to calculate available labour force	Metric, in work-days per year
Access to extension[a]	Access to information from extension services	Binary, 1=access, 0=no access
Access to media[a]	Access to information from media	Binary, 1=access, 0=no access
Access to village head[a]	Access to information from village head	Binary, 1=access, 0=no access
Friends[a]	Number of contacts household discusses agricultural issues with	Metric, in persons
Tpb*belief[a]	Belief that associates agroforestry adoption with certain outcomes, how certain reference groups approve of the behaviour, or that certain control factors are present	Metric, five-point Likert scale
Tpb*scale[a]	Opinion about favourability of belief, motivation to comply, or power over control factors	Metric, five-point Likert scale
Attitude	Farmers' attitude, estimated via structural equation model (SEM)	Metric, in points
SN	Farmers' subjective norm, estimated via SEM	Metric, in points
PBC	Farmers' perceived behavioural control, estimated via SEM	Metric, in points
Intention	Intention resulting from farmers' weighted attitude, SN, and PBC	Metric, in points
Aware	Indicates whether farming agent is aware of agroforestry systems as an agricultural practice	Binary, 1=access, 0=no access
Adopter	Indicates whether farming agent has adopted agroforestry	Binary, 1=access, 0=no access
Income	Household income	Metric, in RWF

Note: [a] *parameterized according to household survey.*

Table 4.2: *Plot agent variables*

Variable	**Definition**	**Scale**
Owner	Indicates farming household who claimed plot	HHID
Size[a]	Land size	Metric, in hectare
Potato wheat	Land cover is potato wheat rotation	Binary, 1=potato wheat rotation, 0=else
agroforestry	Land cover is agroforestry	Binary, 1=agroforestry, 0=else
Agroforestry age	Age of agroforestry system on plot	Metric, in years

Note: [a] parameterized according to household survey.

Further simulation results

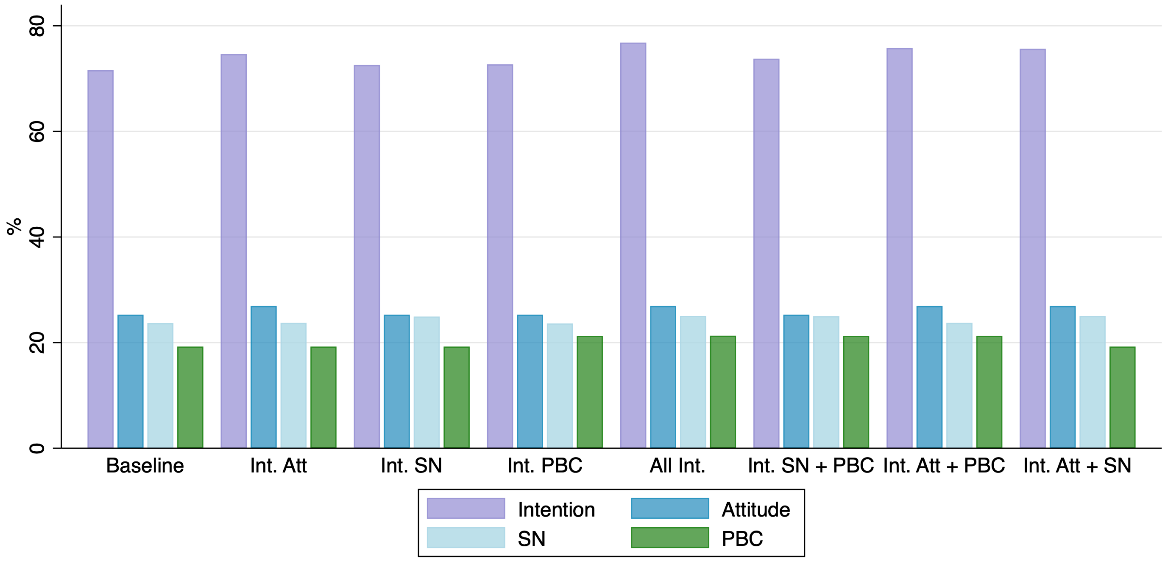

Figure 4.7: *Simulation results: effects of combined interventions*

5. Simulating Agroforestry Adoption in Rural Indonesia: The Potential of Trees on Farms for Livelihoods and Environment

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