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Modelling smallholder land use decision-making with ABM

Assessing the robustness and system assumptions of the LUSES Model

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Details

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Preface

Before you lies my master thesis on the subject of evaluating the LUSES (Land-Use in Social-Ecological Systems) model, which is focussed on decision-making processes in smallholder land use. Along with my internship, this thesis concludes my master's programme Geographical Information Management and Applications (GIMA).

The topic of this thesis combined three subjects of my liking: behavioural theory, land use and (agent-based) modelling. I have always been interested in the ways humans interact, both in relation to each other and in relation to their environment. It was very interesting to learn more about the Consumat theory and about decision-making in land use. I could build on the knowledge gathered in both the GIMA courses and in my bachelor (Human Geography).

I enjoyed the process of writing scripts in Python and learning to work with and code NetLogo models. The process of writing this thesis was strongly self-directed and allowed me to (further) develop my programming, problem-solving and research skills. The majority of this thesis was written with the COVID-pandemic still very much impacting daily life. This meant I worked from home throughout most of the process, which was challenging but also taught me much about staying motivated, perseverance, and about self-management.

I would like to thank my supervisor Erika Speelman for providing this opportunity and for her help with and insight into the LUSES-model. I also would like to thank my supervisor Arend Ligtenberg for sharing his knowledge, especially of the methodological part. Both of you have been a valuable help during the research process, and I enjoyed the conversations about all things ABM. Additionally, I would like to thank my responsible professor Ron van Lammeren, his insights and fresh perspective helped raise the quality of this thesis to a higher level.

Finally, a big thanks to Amber, who wrote her GIMA thesis during the same period. Without her, the process would have been a lot lonelier and more challenging. I look back fondly at our many online meetings, and the occasional real-life study sessions in the kitchen with a cup of tea.

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Abstract

The LUSES-model is an Agent-Based model of decision-making processes in a smallholder farming community, based on the Consumat-framework. A further (quantitative) evaluation of the LUSES-model was required before further development and exploration of the model. In addition to this, further model evaluation could add to the knowledge on the use of the socio-psychological Consumat approach in land use ABMs. This thesis resulted in a quantitative evaluation of the LUSES model, providing a validation of the model output and internal validation to the model by assessing the parameter robustness (including interaction effects) and exploring the model assumptions.

The research is built on a literature study of the most relevant concepts for model evaluation. After preparatory analyses, the robustness of the parameters of the LUSES model was assessed by a One-factor-at-a-time sensitivity analysis. A Sobol' sensitivity analysis was performed to analyse the interaction effects. The system assumptions were explored by analysing alternative scenarios.

The research showed a sensitivity of the model to certain price changes. A large drop of the prices of a crop that used to be steady had extreme effects on almost all output variables: fluctuations and extreme values, especially for more extreme parameter values. The analysis also showed an extreme lack of response to parameter changes in the social need satisfaction variable, though this variable was shown to contribute though interaction effects. The intricacy of this ABM was shown in the Sobol' analysis, which indicated that all main parameters (directly or indirectly) effect almost all output variables. The Existence need satisfaction variable is most influential taking into account interaction effects, the Aspiration variable is most influential without. No abnormalities were found that could not be explained by taking a closer look at the model logic, though the analysis of the system assumptions showed the model should not be used with settings that deviate from the baseline settings or parameter bounds that were tested in the OFAT analysis.

From this can be concluded that the LUSES-model is very sensitive to price changes. This is influenced by the Cognitive effort variable. The Aspiration and Existence need variables have the strongest influence on the output variance. The model is sound, but the use of parameter settings that deviate from the baseline settings should be attempted with caution.

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List of abbreviations

ABM(s)	Agent-Based Model(s)
CHANS	Coupled Human and Natural System
CMCF	Collaboratively managed cleared-field cultivation
CMFB	Collaboratively managed forest-based cultivation
IMCF	Individually managed cleared-field cultivation
IMFB	Individually managed forest-based cultivation
LUSES	Land-Use in Social-Ecological Systems
MAB	Man and Biosphere reserve
OFAT	One-factor-at-a-time
OLS	Ordinary Least Squares
SA	Sensitivity Analysis
SES	Social-Ecological System
SysA	Systems Analysis
TyL	Tierra y Libertad (case-study location)

1 Introduction

1.1 Research context

Agent-Based Models (ABMs) are powerful, versatile tools that are utilized in a broad range of scientific disciplines, amongst others to improve the understanding of complex systems (Ten Broeke et al., 2016; An, 2012). Agent Based Modelling originates from computer science (object-oriented programming, artificial intelligence, and artificial life science) on the one hand and the social sciences (cognitive psychology and game theory) on the other hand (An, 2012). ABMs are strongly computational and experimental in nature, and are used in many disciplines, from ecology to economics and from biology to the social sciences (An, 2012; Liu, 2011). At its core, agent-based modelling means employing computational methods to analyse "dynamic systems of interacting agents" (De Smith et al., 2018, p. 489). Within the social sciences, ABMs are especially useful for the formalization of theories. Compared with mathematical approaches, ABM simulations are less abstract, allow for the inclusion of heterogeneous agents, can more easily be adapted, and can handle parallel processes better. The power of ABMs lies in the capacity to reveal how agent's interactions on the micro level shape overarching patterns on the macro level (De Smith et al., 2018).

Amongst many applications of agent-based models, researchers endeavour to better understand the complex dynamics of land use systems. To study land use dynamics means to study the (often complex) interaction between the biophysical and the socio-economic system. In addition to this interaction between the natural and human system, land use dynamics are influenced by ecological, economic, demographic, and institutional changes, originating from various levels of scale (Verburg et al., 2019; Magliocca, Brown & Ellis, 2014). Land use systems can be referred to as complex adaptive systems, because of the interactions of feedback, learning and adaptation between diverse subsystems (An, 2012, p.25). The ability to model complex adaptive systems makes ABMs well suited to model land use dynamics (DeAngelis & Diaz, 2019).

Land use ABMs mostly focus on the dynamic nature of smallholder farming communities (Mialhe et al., 2012). Global and local change can be challenging to these farming communities. Smallholder farming communities are often less resilient, that is: they have more limited resources and/or are situated in a fragile environment, making it more difficult to adapt to changes (Speelman, 2014, p. 11; Speelman et al., 2014). ABMs can be used as a tool to better understand and forecast phenomena that impact these communities, e.g. biodiversity loss or soil degradation (Mialhe et al., 2012). In addition to this, ABMs can be used to better understand the impact of land use policies on smallholder communities (Acosta-Michlik & Espaldon, 2008). The focus of this thesis is on an ABM of decision-making processes within a smallholding farming community.

In smallholder farming communities, the farmers are the key decision makers. The process of decision-making is therefore an important element of smallholder land use ABMs (Mialhe et al., 2012). The modelling of individual agents is particularly important, for three reasons. First of all, within decision-making processes, individual choices shape the dynamics of the whole (DeAngelis & Diaz, 2019). Secondly, since the characteristics of complex adaptive systems are processes of feedback, learning and adaptation, this stresses the importance of modelling individual agents within decision-making models. ABMs are well suited for this, as they allow for the modelling of individual agents with their own specific characteristics. Thirdly, the representation of the diversity of human agency should be taken into account when modelling decision-making processes. Doing so allows smallholder farmers to have a key role in the mitigation or adaptation to change (Verburg et al., 2019).

The Consumat framework is an example of a theoretical framework which incorporates the diversity of human agency, and does so by including psychological (non-economic) decision-making elements (Jager, 2000). Decision-making processes can be modelled either by using empirical data or by using behavioural theory (Mialhe et al., 2012). The Consumat framework is an example where behavioural theory is used to model the decision-making dynamics of land use ABMs. This framework was developed by Jager (2000) and provides an approach for the modelling of consumer decision making. It emphasizes psychological processes, instead of incorporating just economic and cognitive factors. The Consumat approach is a shift from a purely rational approach (based on the idea of the *homo economicus*) to an approach grounded in socio-psychological theory, taking into account behavioural theory. Thus the Consumat framework provides a more complete framework of decision-making processes (Verburg et al., 2019; Mialhe et al., 2012). The use of the Consumat approach in land use ABMs can provide researchers with new perspectives on the complex interactions within land use systems. Examples of ABM land use studies using the Consumat framework can be found in research by Jaxa-Rozen et al. (2021), Van Oel et al. (2019), Van Duinen et al. (2016), Mialhe et al. (2012), Speelman et al. (2012) and Acosta-Michlik and Espaldon (2008).

For a broader application of the Consumat framework in land use decision-making models, a more thorough, extensive evaluation of these models is needed. Model evaluation (including validation, verification, sensitivity analysis etc.) allows to better compare models, to uncover model mechanics and to improve the system understanding (Verburg et al., 2019). Verburg et al. (2019) emphasize the need to make ABMs easier to compare and generalize in their study on decision-making ABMs. Many land use ABMs are highly case-specific and generalizing these ABMs beyond the original case study is often difficult. Therefore, extensive model evaluation is necessary; further evaluation of the ABMs using the Consumat framework will allow the assessment whether the studies and models can be generalized, and how the Consumat framework can be used for other case studies.

Model evaluation is, however, a complex process for ABMs, for multiple reasons. The complexity of ABMs makes it difficult to present a transparent model analysis and to effectively report analysis results. This causes many to view ABMs as a "black box" (Lorscheid, Heine & Meyer, 2012). In addition to this, two aspects that complicate model evaluation are emergent processes and randomization (De Smith et al., 2018). Since emergent behaviours cannot be predicted, careful analysis is needed to assess whether unexpected results in ABMs are the result of error or emergence (Sætra, 2017). In addition to this, the use of randomization means there are (small) differences between simulation runs. This means many runs of the model are needed to validate ABMs. Analyses of complex ABMs (which have many variables and parameters) can therefore take up a lot of time and resources (Ten Broeke et al., 2016). Thus, ABMs need extensive model evaluations, but this is resource-heavy (especially for large models) and challenging to communicate.

Because of these challenges of extensive model evaluation, many ABMs are not extensively evaluated (De Smith et al., 2018, Lorscheid et al., 2012). The LUSES model by Speelman et al. (2012), which uses the Consumat framework, was published after a qualitative validation. The research by Speelman did not include an extensive validation, e.g. by conducting a sensitivity analysis. The results of the LUSES study show the model could add to the understanding of the land use decisions of farmers in smallholder communities that are faced with global change. In addition to this, the initial results show the use of the social-psychological Consumat framework can be used to explain smallholder land use dynamics. However, the validity of the model should be assessed more extensively before further development and exploration of the model. Aside from providing insight into the model dynamics, further model evaluation could add to the knowledge on the implementation of the Consumat framework.

The LUSES (Land-Use in Social-Ecological Systems) study operationalized an updated version of the Consumat framework (Jager & Janssen; 2012) to model the land use decisions of smallholder farmers. The model is based on research in the case-study location Tierra y Libertad (TyL) in Chiapas, Mexico. Model simulations were compared to empirical data from the case-study. A first qualitative validation of the model showed similarity between the output of the LUSES model and empirical data. In addition to this, the study indicates that the use of the Consumat framework is more suitable to explain farmer's response to change, than common methods that look at past decisions (Speelman, 2014). By further validating the LUSES model, the model dynamics can be further explored. This could add to the understanding of smallholder farmers' responses to economic and institutional change, and to the understanding of dynamics of land use decision-making processes in smallholder farming communities.

To summarize, ABMs are powerful tools to use for the exploration of complex systems like land use dynamics. One of the key aspects of land use dynamics are farmers' decision-making processes. The modelling of decision-making processes can be improved by using social-psychological theory, and by representing the diversity of human agency. An example of a more diverse representation of decision making is the Consumat framework. This framework integrates psychological theory into the decision-making processes, incorporating social, economic, and cognitive drivers. To improve decision making land use ABMs, there is a need for improved model evaluation of these models. Though this is a complex, resource-heavy process, this allows for easier comparison and generalization of ABMs. The LUSES model is in need of additional model evaluation, for example an analysis of the robustness of the model parameters. In addition to this, further verification of the LUSES model allows us to learn more about the use and capacities of the Consumat framework.

1.2 Research aim and research questions

This research will provide a thorough evaluation of the model output and model assumptions of the LUSES model. For ABMs, the sensitivity analysis is the tool that is most commonly used for model evaluation (Ten Broeke et al., 2021, p.2). De Smith et al. (2018) distinguishes two different types of sensitivity analysis. The first use of the sensitivity analysis is to assess the model robustness. Model robustness indicates the sensitivity of the model output to parameter changes. This type of sensitivity analysis is focussed on verification, making sure the "rules" of the model are working as intended. The second use of sensitivity analysis is to determine the effect of changes in the model assumptions on the model output. This use of the sensitivity analysis is more system focussed, providing validation that the model correctly represents the intended theory or phenomenon. The aim of this thesis reflects these two types of sensitivity analysis.

The aim of this thesis is *to provide a quantitative validation of the robustness of the model parameters and the system assumptions of the LUSES-model, with special attention to the implementation of the Consumat framework*. The aim of the original LUSES study by Speelman (2014) was "to explore the ability of the updated Consumat theory to reproduce farmer's land use decisions in a real case". The results of the study were promising, however additional (quantitative) validation of the model is required before further use or development of the model. In addition to this, in a broader sense further analysis of the use of the Consumat framework in the LUSES model could add to the knowledge on the way this socio-psychological approach can be used in land use ABMs. To achieve the formulated research aim, four research question need to be answered. These are as follows:

- RQ1 What are the most important concepts to understand a quantitative evaluation of the LUSES model?
- RQ2 How to adapt the LUSES model to perform a quantitative evaluation
- RQ3 How to assess the robustness of the model output due to parameter settings and their interactions
- RQ4 What impact can be expected by change of 'system' assumptions?

RQ1. Discussing concepts for quantitative evaluation

Answering the first research question provides an overview of the concepts of validation, verification and sensitivity analysis, and discusses how these relate to the evaluation of ABMs. This forms the theoretical background for the next research questions.

RQ2. Adapting the model for quantitative evaluation

Both validating the simulation output and exploring the system assumptions are part of assessing the structural validity of ABMs. Sensitivity analyses are a commonly used technique to assess the structural validity of ABMs (Lee et al, 2015). This second research question discussed how the LUSES model needs to be adapted to allow for the chosen methods of quantitative evaluation.

RQ3. Providing an assessment of the robustness of the model parameters

This research question provides the first part over the overall research aim, by assessing the robustness of the model parameters. This was done by two different types of sensitivity analysis. Sensitivity analyses are useful tools to examine patterns, robustness, or quantify outcome variability (Ten Broeke et al., 2016). To assess the sensitivity of the model output to changes of the main model parameter, a One-factor-at-a-time sensitivity analysis and a Sobol' global sensitivity analysis was performed. Both analysis looked at the main six parameters of the LUSES model.

RQ4. Examining the system assumptions

The fourth research question focuses on the assessment whether specific components of the model "rules" are working as intended. This also includes an exploration of some of the model assumptions. The effect of changes of certain system assumptions on the model output was explored, using simulation experiments (or scenarios). This method is similar to the OFAT analysis; however these scenarios differ in two ways. They assess the influence of more *extreme* changes of the main parameters on the model output (outside the model's parameter bounds), or they assess the influence of changes in (other) model variables that have a key role in the model. This analysis takes a closer look at the following subjects:

1. The cognitive functions of agents (i.e. length of memory),
2. The peer networks (i.e. network sizes; factors for selection peers),
3. Need satisfaction ratios.

1.3 Reading guide

In the next chapter the theoretical framework is outlined. The topics of Agent-Based modelling, modelling land use and the Consumat framework are further discussed. In chapter three the LUSES study is described in detail. Chapter four describes the methodology that has been used for this research. The four research questions are answered in chapter five, discussing the results. After this follow chapters six and seven, which discuss the conclusion and the discussion.

2 Theoretical framework

This chapter provides a theoretical framework to the research of the thesis. Chapter 2.1 discusses the basics of ABMs more extensively, providing insight into what ABMs are, how and why they work and discussing some of the elements of ABMs that are relevant for model evaluation. Chapter 2.2 gives a more in depth overview of the modelling of land use systems, discussing Coupled Human and Nature systems and decision-making theory for land use ABMs. It thus provides insight into the theoretic and academic context of the LUSES model. In chapter 2.3 the Consumat framework is discussed in detail, providing a foundation for the discussion of the LUSES model in the next chapter.

2.1 ABMs in general

One of the earliest Agent-Based models of social science was Schelling's model. Schelling's model is more conceptual and simpler than most ABM's. It is however a great model to use to illustrate the four basic elements of ABMs: agents, environment, rules, and time steps. This model, depicted in Figure 2.1, was used to gain insight into the process of segregation. The model was introduced in 1971 and shows how perceptions on an individual level can lead to segregation on a collective level (Hatna & Benenson, 2012). The agents are symbolized by circles and divided into two groups (indicated by an open or closed circle). The environment is shaped by cells which can house one cell each. The rule (or assumption) of the model is that an agent will move to another cell if the surrounding cells are occupied by a number of same-group agents that is lower than a set threshold.

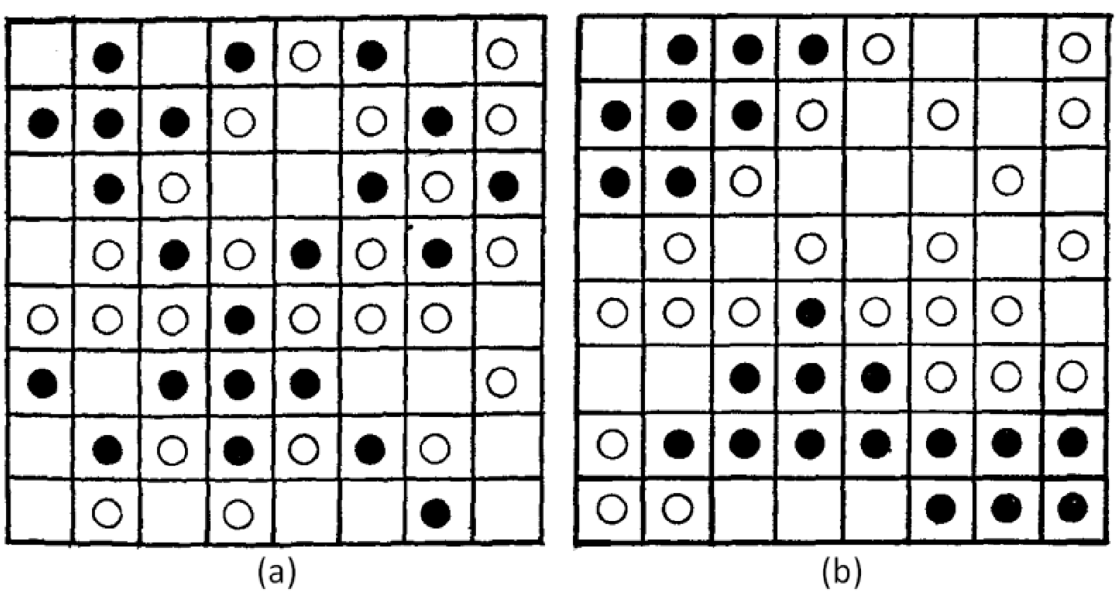

Figure 2.1. *An Agent-Based Simulation of Schelling's model of Segregation, showing the initial condition (a) and the stable pattern after several time steps (b). From Hatna and Benenson (2012).*

With each time step the rule is executed, and after a number of runs a stable pattern emerges. The stable state of the model is shown in Figure 2.1b.

As discussed in the introduction, we can learn about the dynamics of complex systems through the analysis of simplified simulations such as Schelling's ABM. In Agent-Based Modelling both the system (macro level) and the agent (micro level) are studied, as well as the dynamic between them. As De Smith et al. put it: "Agent-based models seek macro-level understanding based on micro-level processes" (2018, p. 489). ABMs are especially useful to explore the interactions and behaviour of agents (Zhang, Li & Zhang, 2020). The *modelling* of ABMs can be referred to as individual-based modelling, since its focus is on the agent and not on the system (Sætra, 2017). At the same time, the *analysis* of ABMs is aimed at the understanding of both systems and behaviour. This makes ABMs useful tools to detect emergence in complex systems, emergence being the phenomenon where something happens on system level that is not detectable on agent level (Sætra, 2017).

Model validation and verification means testing whether the model simulates the phenomenon appropriately and testing whether the theory is translated correctly into code (De Smith et al., 2018). This is complex for ABMs for multiple reasons, one being that emergent processes are difficult to distinguish from errors in the model. In essence emergent processes are patterns visible on the level of the collective that come into being through the interactions of agents (De Smith et al., 2018). A second reason of the complexity of ABM validation and verification is that ABMs often use random numbers. Randomization is used to account for variables that are unmeasurable or random, and this causes output to (slightly) differ for each simulation (De Smith et al., 2018). The concepts of verification and validation are discussed in depth in chapter 5.1.

Sætra (2017) argues Agent-Based Modelling cannot easily be classified as either quantitative or qualitative research, nor is it easily placed within alternative classifications. He argues Agent-Based Modelling is "*completely dependent on the mix with other methods in order to evaluate and make sense of the results it provides*." (2017, p. 29). Therefore he classifies Agent-Based Modelling as a mixed-methods methodology (also referred to as triangulation or multi-method research). An example of the use of triangulation for Agent-Based Modelling is the comparison of theory, simulation data and historical records (Sætra, 2017). It is however important to note that, while Agent-Based Modelling can be considered a mixed-method approach, the model calibration and verification relies heavily on sensitivity analysis (which are quantitative in nature).

De Smith et al. (2018) state ABMs can be divided into two main categories: predictive and explanatory models. Explanatory models try to provide a better understanding of processes, for example the goal of an explanatory ABM could be to model agents' behaviour in order to reproduce (real-life) patterns in the model output. The focus is on exploring theory and better understanding systems or processes. Predictive (or descriptive) models are used to extrapolate trends and patterns, often by looking into different scenarios. Where explanatory models seek to reproduce observed patterns in the simulation output, predictive models seek to reproduce the observed system (De Smith et al., 2018). ABMs that are used to analyse land use decision-making are often explanatory ABMs: the aim is to gain a better understanding of a complex system.

One of the limitations of ABMs is how the inherent model complexity makes it difficult to present a transparent model analysis and to effectively report analysis results. When ABMs are used to simulate complex systems, the models are a lot more intricate than Schelling's example. Lorscheid et al. (2012) state: *"The predominant complexity of simulation data makes it difficult to be conclusive without providing too many details and distracting from the main findings*" (p. 23). One of the downsides of the ability of ABMs to simulate highly complex and dynamic problems is the challenge it poses when communicating the analysis results. When publishing analysis results, practical limitations in terms of word limits restrict the presentation of an all-encompassing overview of the ABM.

2.2 Modelling land use dynamics

2.2.1 Decision-making theory within land use research

Hubert et al. (2018) compared studies of heterogeneous decision-making processes in ABMs of (European) land use systems. In land use ABMs, model comparisons and reviews are common (Huberts et al., 2018). They state how, because of a lack of empirical data, explanatory models of land use systems are very important. Explanatory aims are the most common for ABMs: a model is used to assess whether a phenomenon can be explained (Ten Broeke et al., 2021; Sætra, 2017). These models allow for the evaluation of policies, and are particularly powerful because of the ability of ABMs to provide understanding of individual behaviour in response to changes of a complex system, on both a micro and a macro level (Hubert et al., 2018).

Beedell and Rehman (2000) notice a shift in land use research in the UK, from a more descriptive research-focus up to the 1980's, to a more explanatory research-focus towards the year 2000. This shift was pushed by demands from policymakers, who pressed for methodologies that could be repeated nationwide and that could give a prediction of landscape changes. This influence from policymakers encouraged merging research on landscape change studies (often time series data) with attitudinal/motivational studies. The latter caused research to not only consider socio-economic factors, but also take into account farmer's willingness and ability to change and any constrains that could affect this. This inclusion of the concepts like 'willingness to change' originated from social theory. In socio-psychological models, variables such as likes, beliefs and preferences were implemented and found to have explanatory power (Beedell and Rehman, 2000). Amongst other studies, this is reflected in the LUSES model, which takes into account farmers' land use preferences in the decision-making model.

The shift from a descriptive research focus to a more explanatory focus within land use science in the UK can also be observed on a global level. The combination of environmental and economic change on a global level, and transitions in land use and livelihood on a local level, stress the importance of the ability to globally assess local causes and results of transitions in land use dynamics in a systemic way (Magliocca, Brown & Ellis, 2014, p. 1). This will allow for a better assessment of what is needed to properly manage such transitions and can provide better guidance to local decision-making. Many land use studies are local, focussed on one or several locations. Though efforts are made to analyse common dynamics, knowledge on land system change remains fragmented. Magliocca, Brown and Ellis (2014) therefore stress the importance of generating knowledge that can be generalized.

The Consumat framework provides a theory that allows for the study of the choices of local agent in response to local or global factors. However, this model needs to be tailored to fit specific case-studies and focusses mainly on economic (and not environmental) change. The LUSES study is specific for the TyL study area in terms of local responses to drivers. Yet, the LUSES model showed explanatory power for the TyL context when it comes to the influence of social organization and institutions as a reaction to (economic) change.

2.2.2 Social-Ecological Systems

Land use dynamics can be described as simulations of Coupled Human and Natural Systems (CHANS), especially if the model considers environmental or climactic feedback. Ferraro, Sanchirico and Smith describe CHANS as "*complex, dynamic, interconnected systems with feedback across social and environmental dimensions*" (2019, p. 5311). The framework of the Social-Ecological System, or SES, is related to the concept of CHANS (Liu et al., 2021). Liu et al. (2021) state concepts like SES, CHANS or 'human-environment systems' are often used interchangeably within literature. All three concepts emphasize the way human and natural systems are intertwined (An, 2012), but formally 'CHANS' can be used as the overarching concept, including all human dimensions: social,

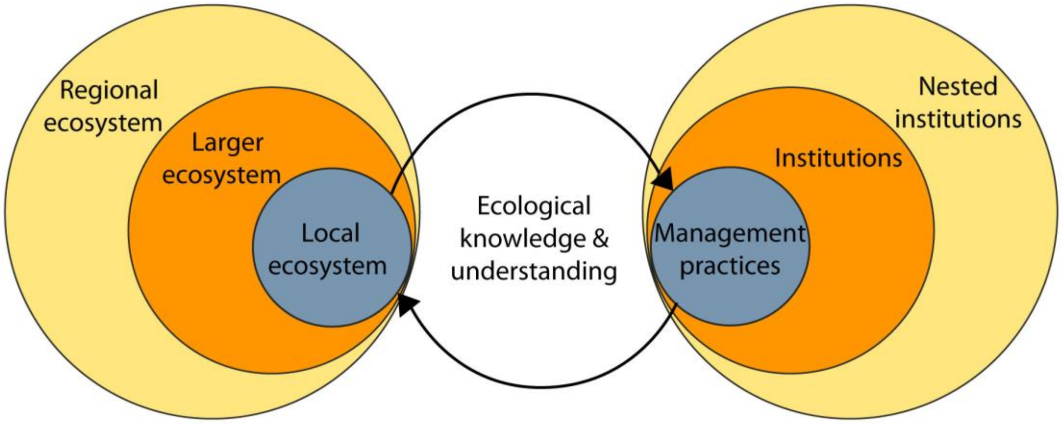

Figure 2.2.2. *A graphic representation of the analysis of linked social-ecological systems. From Colding and Barthel (2019).*

economic, institutional, etc., and all natural aspects: environmental, climatic, hydrological, etc. (Liu et al., 2021).

In the LUSES research, the concept of Social Ecological Systems is used. The SES framework is used to study the impact of natural and human systems on the resilience and performance of local resource management (Colding & Barthel, 2019). An example of a SES framework can be seen in Figure 2.2.2a.

The SES framework is very useful when trying to understand complex adaptive systems. Complex adaptive systems are systems that have "*heterogeneous subsystems or autonomous entities, which often feature nonlinear relationships and multiple interactions (e.g., feedback, learning, adaptation) among them*" (An, 2012, p. 25). Most land use ABMs feature complex adaptive systems. Complex systems can be recognized by path-dependence, self-organization, and emergent properties, amongst others. Instead of focussing on predicting or controlling complex system, it is thought to be better to put emphasis on understanding complex systems such as land use systems (Ten Broeke et al., 2016; An, 2012).

For the TyL case-study, Speelman et al. (2014) studied the adaptive capacity of farmers when confronted with economic and institutional drivers. The concept of SES can be recognized immediately in the name of the LUSES model: the 'Land-Use in *Social-Ecological Systems*' model. Though the focus of the first TyL study by Speelman et al. (2014) was more on aspects of social organization and institutional change, one of the six attributes that were used to assess adaptivity were natural resources. The concept of SES can also be noticed clearly in the graphical overview of the conceptual model of the LUSES model (see Figure 2.2.2b): this explicitly mentions both the social and the ecological subsystem. Though some of the ecological elements are not (yet) incorporated in the LUSES model, the incorporation of the SES concept emphasizes the importance of landscape composition and geographical embeddedness.

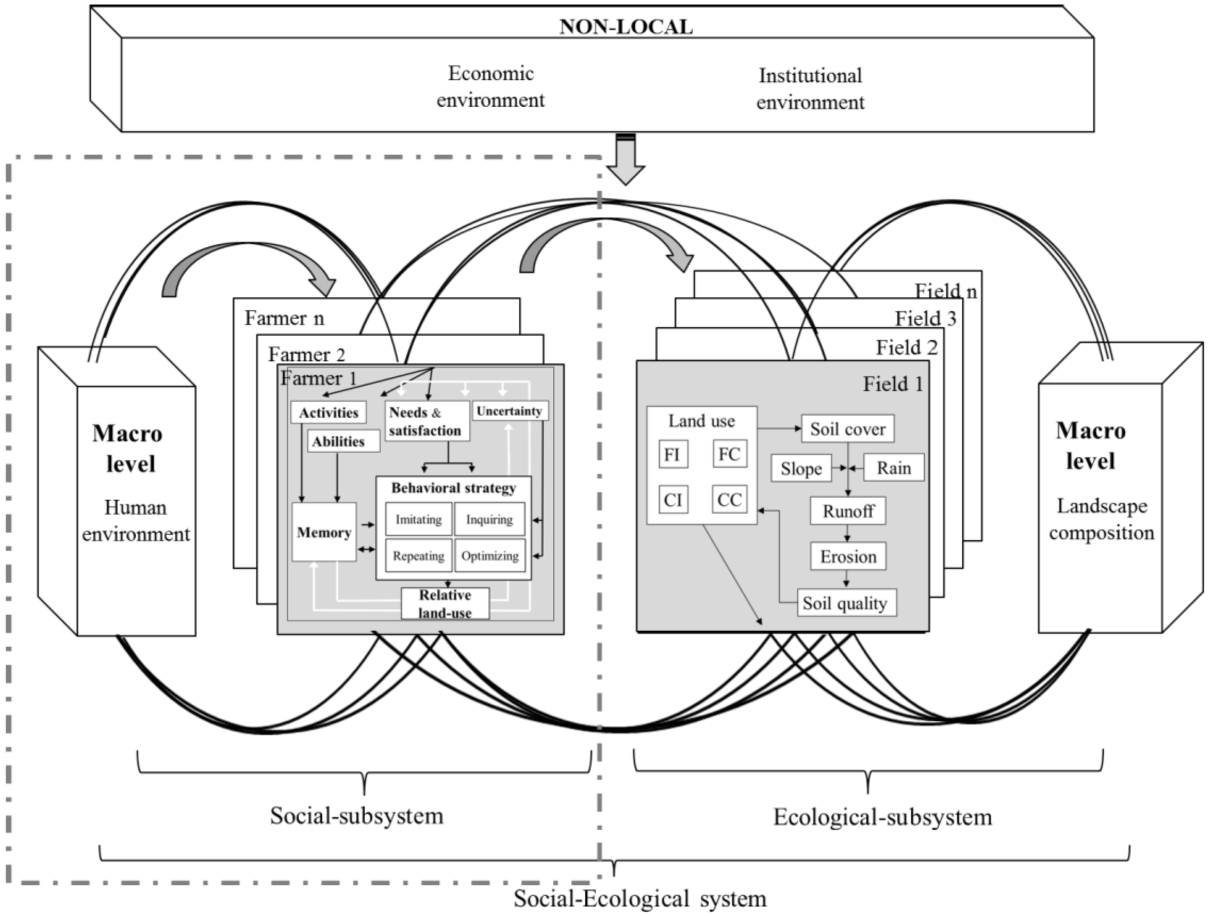

Figure 2.2.2b. *A graphic representation of the conceptual model of the LUSES model. From Speelman (2014, p. 124)*

2.2.3 Land use ABMs and decision-making theory

An (2012) created an overview of nine generic decision models/rules that are used in ABMs depicting CHANS (see table 2.2.3 on the next page). Decision-making models can use a combination of these nine types. The LUSES model, for example, combines a microeconomic model with sociopsychological theory. In addition to this, the LUSES model was made using empirical data from the TyL case study, and in some places makes use of empirical rules to reproduce a phenomena. The model also includes institution-based rules: elements of the model represent the influence of subsidies and environmental standards.

For microeconomic models, An (2012) warns modelers to be aware of the limitations of these types of models: modelling choices are often based on theory *and* on the modelers perception of the modelled phenomena. It is important to be aware of the latter. For psychosocial and cognitive models, An advises modelers to carefully consider the impact of social network on decision-making. For models based on empirical- or heuristic rules, An points out these type of models focus strongly on recreating a phenomenon, leaving the question "why?" unanswered.

Table 2.2.3. *The nine types of decision ABMs according to An (2012, p.28-32).*

Model	Foundation for decision-making
microeconomic models	Resources (maximizing profit); rational choices; bounded rationality.
space theory based models	(Relative) positioning of locations/objects of interest; rational choices; sometimes includes communication.
psychosocial and cognitive models	Cognitive maps; behavioural drivers (e.g. social structures, agents' intentions or aspiration); social networks.
institution-based models	Institutional (social) norms.
experience- or preference-based decision models	Based on data or stylized facts; dynamic rules; sometimes combines algorithms with expert knowledge and/or fuzzy logic.
participatory agent-based modeling	On-site decision-making by stakeholders (non-specialists); role playing real stakeholders.
empirical- or heuristic rules	Based on data grounded in theory (e.g. statistical analysis); focus on reproducing phenomena, not explaining.
evolutionary programming	Algorithms focussed on copying and mutating agents' characteristics
assumption and/or calibration-based rules	Using (untested) hypothetical rules to operationalize a model

2.3 The Consumat framework

The Consumat framework has already been briefly introduced. The next section provides a further discussion of the Consumat framework, by placing it in the context of socio-psychological and economic theory. After this, the main parts of the Consumat framework are discussed, illustrated by schematic representation of the Consumat meta-model of behaviour. Additionally, the four behavioural strategies will be discussed more in depth. To conclude, some ABM land use decision simulations will be discussed and compared with the LUSES study.

2.3.1 The Homo Psychologicus

The focus of this framework is on consumer behaviour: hence the name: Consumat (Jager et al., 2000). It is however used in various case studies that are not focussed on consumers, as discussed in the previous section.

To paint a picture of the background of the model regarding decision-making theory, we go back to classical economic theory. Within this realm of through, humans are seen as purely rational beings: behaving with their self-interest at heart. From this emerged the concept of the *Homo Economicus*, which depicts humans conducting optimizing behaviour (Jager et al., 2000). This can also be referred to as the rational-actor approach (Jager, Janssen & Viek, 2001). The rational-actor approach implies people make choices with perfect knowledge and optimizing behaviour. This optimizing behaviour has been used to model decision-making processes in Agent-Based models. The idea of the Homo economicus and the rational-actor approach are however disputed in more recent research (Jager et al., 2000).

A common critique on this approach is that people often do not have perfect knowledge, and their memory is not flawless. In addition to this, there are two ideas from social-psychological behavioural theory that should be taken into account when thinking about decision-making processes. Firstly, decision-making is not only governed by optimizing behaviour but is also shaped by routines and habits. Secondly, the optimizing mindset is contradicted by social psychological theory, for "*people do not always optimize their outcomes, but often engage in satisficing behaviour*" (Jager et al., 2000, p. 360). This satisficing behaviour is a form of social processing. This means people use information about the behaviour of others for their decision-making processes. Social satisficing behaviour is more likely to happen when people face uncertainty (Jager et al., 2000). These aspects of social-psychological theory are taken into account in the Consumat framework, in order to more accurately depict decision-making processes.

In contrast with the *Homo Economicus*, the Consumat framework incorporates the idea of the *Homo Psychologicus*. Jager et al. (2000) combined ideas from psychological theory and economical behavioural theories to develop the *Homo Psychologicus*, taking into account processes of imitation and social comparison. At the core of the Consumat model are the four behavioural strategies agents can partake in, allowing for diversity of human decision-making compared with the rational-actor approach which defines one way of decision-making for all agents. In the Consumat framework, two main factors weigh in to determine what will be the basis of agents' decision-making strategy: the satisfaction of agents' needs and the uncertainty of agents. These two factors determine the choice of one of four behavioural strategies: imitating, repeating, optimizing, or inquiring behaviour (Jager & Janssen, 2012).

Thus the Consumat approach allows for the integration of psychological theory when modelling decision making processes. The framework not only allows for a more accurate representation of reality, the four behavioural strategies also allow for a more diverse representation of decision-making processes. An additional strength of the Consumat framework is the way it brings together different parts of behavioural theory, providing a framework of simplified theories where many behavioural theories explain only parts of processes (Jager et al., 2000, p. 362). In the next section the Consumat framework is further explained, using a schematic representation of the Consumat framework.

2.3.2 The Consumat conceptual model

This paragraph covers a discussion of the main parts of the Consumat framework, as illustrated by the schematic representation of the Consumat approach (see figure 2.3.2 on the next page). The conceptual model can be divided into two levels: the general or collective processes, and the agent processes.

The figure shows the level of the collective (i.e. the macro level) on the left, and the level of the agent (i.e. the micro level) on the right. The driving forces of both levels make up the setting of the behavioural model. On the left the macro level depicts elements such as technical, economical, or institutional developments or constraints on the level of the collective. These influences on the macro level impact the micro level of each individual agent, as depicted on the right side of the figure. On the level of the individual, driving forces are the agents' needs, consumption opportunities, abilities for consuming, satisfaction, uncertainty, and the behaviour of other (similar) agents (Jager, 2000, p. 205). The choice for a certain behavioural strategy depends on these driving forces.

The micro level (the level of the agent processes) has four major elements: 1) changes over time, 2) uncertainty and need satisfaction, 3) the selection of behavioural strategies, and 4) memory. These will be discussed next.

The first thing to discuss is that the Consumat model considers changes in consumer behaviour over time. This is depicted in the main circular arrows. This indicates that a certain choice (opportunity consumption) will result in changes on the human-natural environment and will influence future choices. On the top of the submodel depicting the micro level driving factors, four factors are shown that are influenced this way. These are opportunities, opportunity consumption similar to others, abilities, and the level of needs (satisfaction); all influenced (directly and indirectly) by previous consumption. In this way, time is taken into account in the conceptual Consumat model.

The second element to be discussed are the uncertainty and need satisfaction. Agents' needs satisfaction is a result of the fulfillment of needs. Humans have different types needs (as described in e.g. Maslow's theory of the hierarchy of needs). For the LUSES model agents' needs are generalized into three categories: existence needs, social needs and personal needs. Together, these needs form the overall need satisfaction of an agent (Alonso-Betanzos et al, 2017). In the

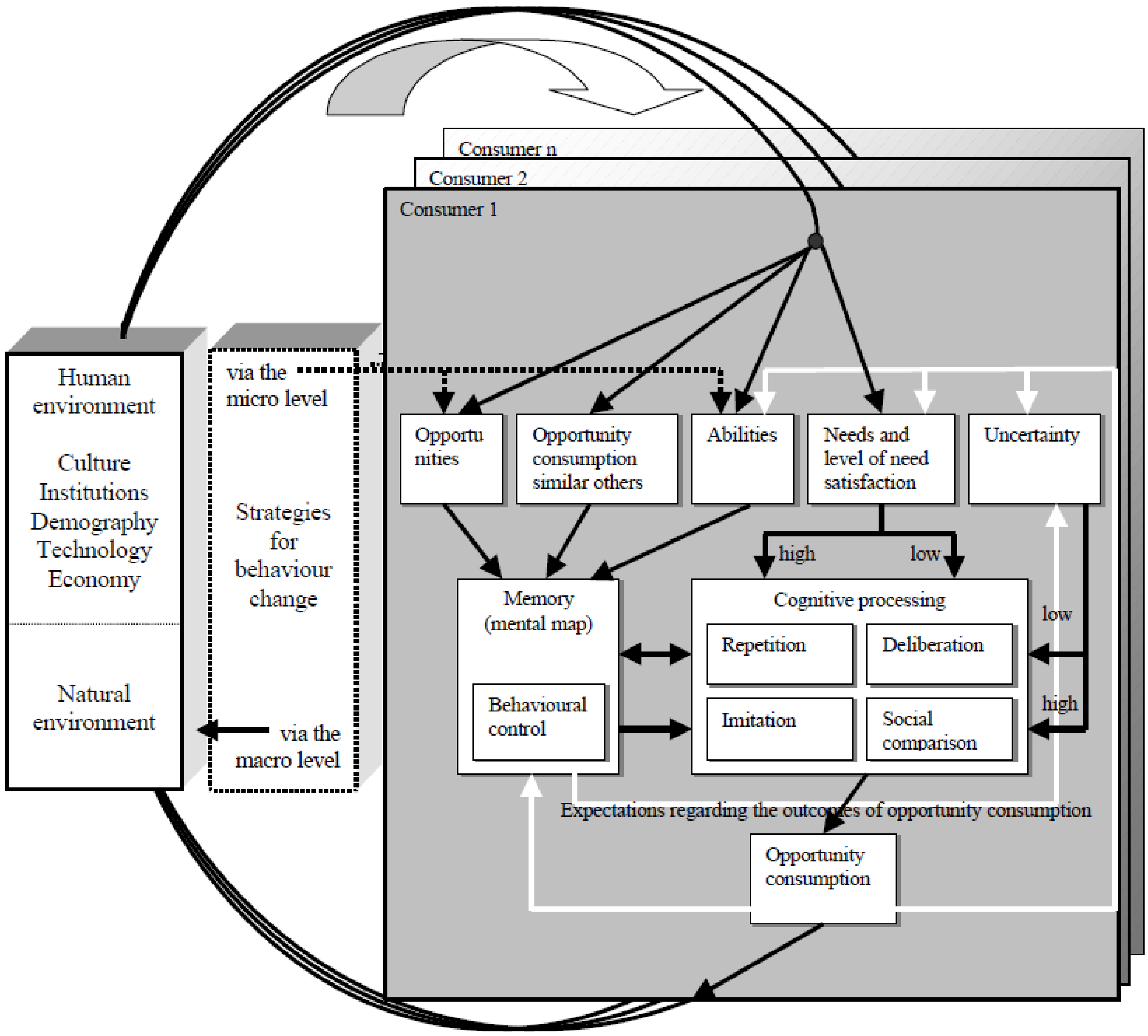

Figure 2.3.2. *The conceptual model of consumer behaviour according to the Consumat approach. From Jager (2000, p. 97).*

conceptual Consumat model, this distinction between different types of needs is left out. The (level of) needs satisfaction and the uncertainty are depicted on the top right of the micro level. Agents' need satisfaction is based on the satisfaction of their needs compared to the need satisfaction minimum. The need satisfaction is updated based on the consumption of opportunities. Agents' uncertainty is indicated by the difference between the expected need satisfaction and the *actual* need satisfaction. If the difference exceeds the uncertainty tolerance level, agents will adopt a different behavioural strategy.

The third major part of the model is the selection of a behavioural strategy. The adaptation of a certain behavioural strategy (repetition, deliberation, imitation, or social comparison) is referred to as cognitive processing (Jager & Janssen, 2012). As discussed, the choice of a behavioural strategy depends on the satisfaction of agents' needs and the experienced uncertainty of agents. Agents who are more uncertain than their tolerance level will engage in social behavioural strategies, otherwise the agent will engage in individual behavioural strategies. If agent's need satisfaction is above the minimum need satisfaction level, the agent will engage in automatic behaviour. If the agent's need satisfaction is below this threshold, the agent will engage in reasoned behaviour (Jager, 2000, p.107). The differences between these four behavioural strategies are discussed in the next section.

When engaging into these behavioural strategies, the cognitive function (or memory) of agents is relevant, allowing agents to recall behaviour of other agents and outcomes of past choices (Alonso-Betanzos et al, 2017). The third (and last) major part of the Consumat model is this function: the memory of agents. Individuals have a cognitive function, or: mental map, which allows them to remember information on opportunities, abilities, and other agents' characteristics. Thus, as is depicted on the left side of the overview of micro driving forces, the choice and outcome of the behavioural strategies depends on information and expectations about the environment (Jager et al., 2000, p. 358).

Agent's mental map influences and is influenced by abilities, need satisfaction and uncertainty, through the opportunity consumption (indicated by the white arrows in the conceptual model). There is a direct influence of the mental map on uncertainty because of agent's expectations regarding the outcomes of the opportunity consumption. For the reasoned behavioural strategies (deliberation and social comparison) agents memorize their own (past) choices, as well as the choices of others. Agents can also use their mental map to memorize the potential need satisfaction of certain choices. In the next section, the behavioural strategies are further explained.

2.3.3 Behavioural strategies

As mentioned above, are the core of the Consumat framework are the behavioural strategies (repetition, deliberation, imitation, and social comparison), which are based on the level of need satisfaction and the level of uncertainty. On a theoretical level, a distinction can be made between automated versus reasoned, and individually versus socially determined behavioural strategies. This is schematically depicted in figure 2.3.3. These behavioural strategies will be discussed next.

The behavioural strategy of repetition indicates habit formation. This is an automated, individual process, which happens if the agent is satisfied and certain. Agents will repeat the previous choice (indicated in figure 2.3.2 by the link to the *mental map*).

In the updated Consumat framework the consumer behaviour of *deliberation* is renamed as *optimizing* behaviour, to better reflect the focus on optimizing behaviour, similar to the *Homo Economicus* (Jager & Janssen, 2012). The agent will choose optimizing behaviour if they are

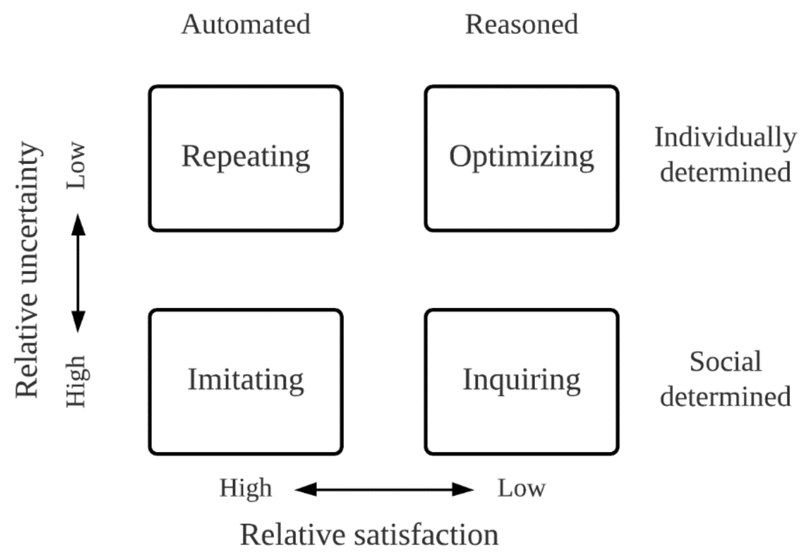

Figure 2.3.3. *The four behavioural strategies in relation to uncertainty and satisfaction, and with a distinction of concept from social theory.*

dissatisfied and certain. Optimizing behaviour is individual and reason based. Agents assess the consequences of their options within a certain timeframe; after a rational assessment of their options they will choose the behaviour that has the best expected outcomes (Jager et al, 2000; Jager, 2000). For this behavioural strategy, the agent gains satisfaction from the expected results of a choice.

If the consumer is satisfied but uncertain, they will show *imitation* behaviour. This means they will copy the choice of a fellow, similar, agent. The choices of other agents are remembered, as indicated by the link to *mental map* (Jager et al., 2000). Imitation behaviour is derived from social learning theory and indicates automatic social processing (Jager, 2000).

Similar to the concept of deliberation, *social comparison* is re-named in the updated Consumat framework. Social comparison is now referred to as *inquiring* behaviour, to give a better indication of the deliberate process of asking about others' behaviour (Jager & Janssen, 2012). Inquiring behaviour is performed by agents that are unsatisfied and uncertain. It is derived from social comparison theory, and it indicates reasoned social processing (Jager, 2000).

To summarize, the four behavioural strategies are determined by agents' uncertainty and needs satisfaction. A distinction can be made between reasoned and automated behavioural strategies, as well as between individually determined and socially determined behavioural strategies.

2.3.4 Consumat in decision-making land use studies

Examples of ABM land use studies using the Consumat framework can be found in research by Jaxa-Rozen et al. (2021), Van Oel et al. (2019), Van Duinen et al. (2016), Mialhe et al. (2012), Speelman et al. (2012) and Acosta-Michlik and Espaldon (2008). The study by Acosta-Michlik and Espaldon is very similar to that of Speelman (2014), and will shortly be described below. Acosta-Michlik and Espaldon

(2008) used an ABM to learn more about the vulnerability and adaptation of farming communities in the Philippines. The focus of the study was on global changes of environmental and economic factors, and how this affected farmers' vulnerability. They modelled socio-economic and ecological elements, and the way global factors influenced these, to improve understanding of adaptive behaviour. The Consumat framework was used, and the four cognitive strategies of Consumat were adapted to fit the specific decision-making process. The strategies of repetition, imitation, inquiry, and optimization were brought back to just 3 strategies, by combining the strategies of imitation and inquiry. One of the conclusions of the research was that social networks can be used to increase the adaptive capacity of farmers, when confronted with global changes. Farmer adaptive capacity was limited due to lack of money and information. The social networks of farmers were found to mostly extend to relatives and neighbours, however if these social networks can be broadened to include sources of technical knowledge, this is expected to improve farmers' adaptive capacity (Acosta-Michlik & Espaldon, 2008). This study is an example of the implementation of the Consumat framework in research on land use decision-making.

In this chapter, this research was placed within the context of literature on ABMs, the modelling of land use and the Consumat framework. In the next chapter, the TyL study and the LUSES model are discussed.

3 The LUSES study

The following description of the LUSES study is based on chapter two and chapter six from the PhD dissertation "Gaming and simulation to explore resilience of contested agricultural landscapes" by Erika Speelman (2014, p. 120-154). Chapter two of Speelman's work is based on research by Speelman, Groot, Garcia-Barrios, Kok, Van Keulen and Tittonell (2014). As part of this study, empirical data was gathered in Tierra y Libertad (TyL), a smallholder farming community in Chiapas, Mexico. Speelman presents a driver-response reconstruction of the responses to economic and institutional change. This chapter is the source of the introduction of the case-study, section 3.1. Chapter six of Speelman's work is based on research by Speelman, Jager, Groot, Garcia-Barrios and Tittonell (2012). Chapter six introduced the LUSES model, and discusses the model development, a qualitative validation of the model and further model explanation. This is discussed in section 3.2.

3.1 Tierra y Libertad

The Tierra y Libertad community is a young community that has had to face great economic and institutional changes, which especially impacted the prices of their produce (Speelman, 2014, p. 21). In the following section the geographical and historical context of TyL is discussed, and economic and institutional drivers of change are discussed.

3.1.1 Geographical location

Tierra y Libertad is a remote community in Chiapas, Mexico. At the time of the study by Speelman (2014) the population was estimated to be around 750 persons (with an average of 24 years). TyL is situated near the mountain ridge of the Sierra Madre de Chiapas. The community spans about 3200 ha, between an altitude of 900 and 1500 meters above sea level. This is hilly terrain; about 80 percent of the territory is under forest cover. At the time of the study the most common land use types were pasture-based livestock production, staple food production (i.e. maize and beans) and forest-based production (coffee and palm). The 'La Sepultura' Man and Biosphere (MAB) Reserve was established in 1995 and covers the whole of TyL (see Figure 3.1.1). Within the reserve, core zones are assigned where human activity is forbidden. In the rest of the reserve (the buffer zone) activities are allowed within the bounds of certain restrictions (Speelman et al., 2014).

Figure 3.1.1. *The geographical location of TyL and the reserve La Sepultura (core areas are marked in dark green). From Speelman et al. (2014, p. 33).*

3.1.2 Historical context of TyL

The exploitation of timber drew people to TyL in the early 1960s. Their earnings at a private sawmill were supplemented by selling (ornamental) leaves from wild Camedor palms. The land that was cleared by the sawmill was cultivated; the main crop was maize for home consumption. In 1972 the sawmill was closed, and 2200 ha of land were made available to 101 households by the national government. The legal form of land ownership was the '*ejido*' system. This Aztec system had been re-introduced in the 1930 and revolves around shared management of communal resources where a fixed number of households have land rights. These households are called '*ejidatarios'* and they can weigh in on community decisions, as opposed to the '*pobladores'* (households without land rights). The *ejido* was expanded in 1986 by the national government, adding 1000 ha and 22 *ejidatario* positions to the *ejido*. The ejido system was however seen as being inefficient and unproductive compared to private ownership, and due to a shift towards more neoliberal politics in 1992, ejidos were allowed to make the shift towards individual land rights.

After the closing of the sawmill, the population of TyL could be roughly divided into households that relied on palm extraction (and were less interested in land rights) and households that concentrated their efforts at agricultural practices. The latter obtained more (and less forested) land. In 1995 the Man and Biosphere (MAN) reserve was established. The restrictions that followed from being situated within the La Sepultura reserve (and the minimal consideration of the communities' interests) caused a conflict between the Reserve authorities and the community. Eventually a program was launched by an NGO (with financial support of the Reserve), with the aim to improve local social organizational structures and collective decision-making. This project was successful and the TyL community requested the support of this NGO for several other projects.

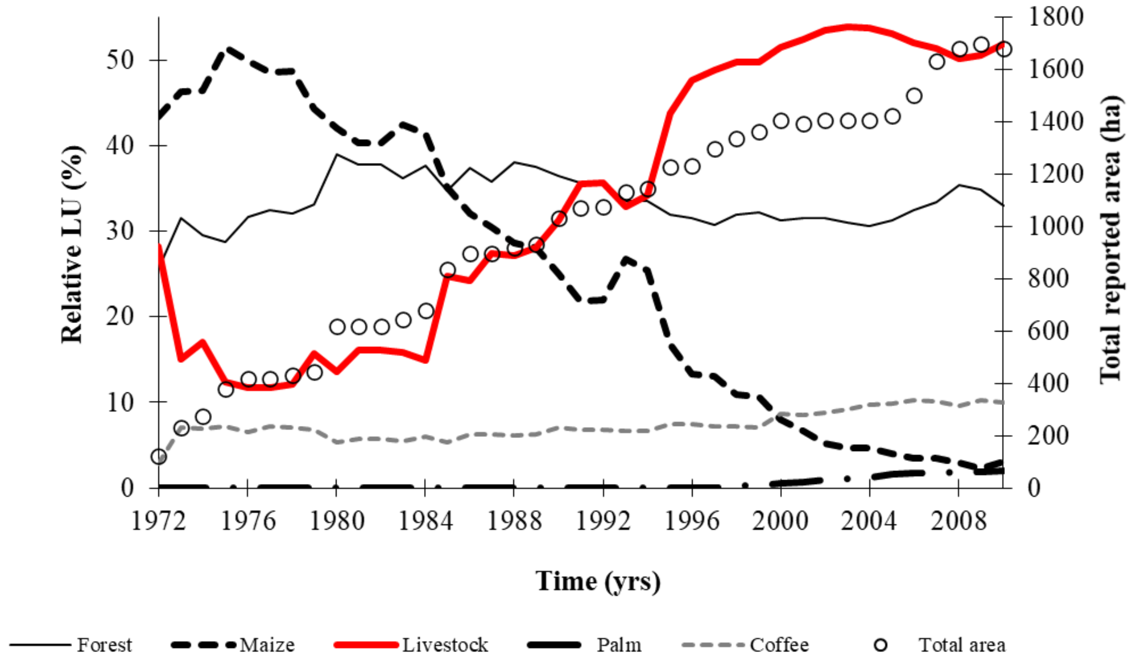

Figure 3.1.2. *Relative land use of the TyL community, from Speelman*

As mentioned above, at the time of the study the most common land use types were pasture-based livestock production, staple food production (i.e. maize and beans) and forest-based production (coffee and palm). Maize and beans are produced for home consumption, whereas coffee and palm leaves are sold in one of the nearby towns and to an export company, respectively. See Figure 3.1.2 for an overview of the common land use types in TyL throughout the years. The next section discusses the translation of the case-study data into an ABM for Land use in Socio-Ecological systems.

3.2 The LUSES model

This section will provide a short overview of the most important elements of the model. This section is structured roughly according to the ODD+D principle and will discuss the following topics: 1) Purpose, 2) Entities and state variables, 3) Process and basic principles, 4) Submodels. The full ODD+D overview can be found in the Appendix I.

3.2.1 Purpose

For the original study, the LUSES model was developed in Netlogo 4.1.3 (Wilensky, 1999). It has been transformed to a more recent version of NetLogo (version 6.0.4) for the purpose of this research. The LUSES model has an explorative design and is explanatory in nature. The aim of the LUSES-model is *"to create a simple yet comprehensive simulation tool for the analysis of coupled socio-environmental systems in agricultural landscapes grounded in sound social behaviour theory* *and parameterized with empirical data*" (Speelman, 2014, p. 145). Empirical data was gathered, mapping the trends and dynamics of land use within the TyL community and the price variations of different crops. The social behavioural Consumat framework was adapted to fit the simulation of land use systems.

A qualitative exploration of the LUSES model was performed, using empirical land use data from 1960 to 2010. Four main themes were explored in simulation experiments: 1) collaborative land use benefits, 2) landscape composition, 3) economic and institutional scenarios, and 4) relative personal, social and existence needs. For all simulation experiments the model was run for 50 time steps and repeated 100 times.

3.2.2 Entities and state variables

There are two entities in the model: the agents and the environment. Agents are representations of farmers, who are the head of a household. The base number of farmers for the LUSES simulation is 100, and each farmer is the head of a household of five (see Table 3.2.2 for the variables of the LUSES model). The environment can be broken up into the local and the global environment. The local environment indicates the characteristics of the individual patches of land. The local environment encompasses 1681 patches of land, each representing 1 ha. A patch of land can be owned by *one* agent and can hold *one* of the four types of land use. The four different types of land use are:

Table 3.2.2. *State variables of the LUSES model, table adapted from Speelman (2012, p.* 127&145)

Level	Variable	Range	Value in experiments
Agent	Ambition level	0-1	Random
	Uncertainty tolerance level	0-1	Random
	Cognitive effort	1-10	Random
	Relative existence need importance	0-1	0.33 OR random 0.8-0.99
	Relative social need importance	0-1	0.33 OR random 0.1-0.05
	Relative personal need importance	0-1	0.33 OR random 0.1-0.05
Environment	Land-holdings per agent	1-1676	1-254
	Household size	2-9	5
	Number of agents	6-1681	100

1) individually managed cleared-field cultivation (IMCF),

2) collaboratively managed cleared-field cultivation (CMCF),

3) individually managed forest-based cultivation (IMFB), and

4) collaboratively managed forest-based cultivation (CMFB).

The 1676 patches of land are allocated to the farmers using a distribution similar to the TyL case study location. One of the landholdings of each farmer is selected as the location of their household. The global environment can be described as the state variables that affect all agents. Part of the global environment are the price trajectories of the different land uses. The simulations were run with time steps of one year, for a total amount of 50 years.

3.2.3 Process and basic principles

The LUSES model has many submodels, the most relevant of these are: income calculations (cognitive function), peer selection, need satisfaction ratios and behavioural strategy selection. Before discussing these submodels, an overview of the overall process and the basic principles of the ABM will be given.

On the next page, Figure 3.2.3 provides an overview of the order of processes. At the beginning of each year, the lists are updated: the land use types of all patches of land are updated to the land use selected at the end of the previous year, and the farmers' incomes are calculated. If the farmers have no savings, they will be left out of the simulation. New peers are selected based on several categories of similarity: the selected land use, the land use preference, savings, land holding and distance. The expectations of the selected peers are used in some of the following calculations. After peer selection, the need satisfaction will be calculated (specifically the existence need, social need and personal need), as well as the uncertainty, uncertainty ratio and the behavioural options. For agents that had "inquiring" or "optimizing" behaviour in the last year, the expected profit for currently selected land use types will be taken into account as well when calculating the need satisfaction.

Agents make different calculations based on their need importance, cognitive effort, ambition level, uncertainty tolerance level, the price data, and their peer network. The uncertainty and satisfaction ratios determine what behavioural strategy will be chosen: optimizing, inquiring, repetition or imitation, as discussed in the section on the Consumat framework. If the potential satisfaction of needs has not yet been calculated, this will be calculated now. Based on this, the behavioural strategy and the precious calculations, next year's land use will be calculated.

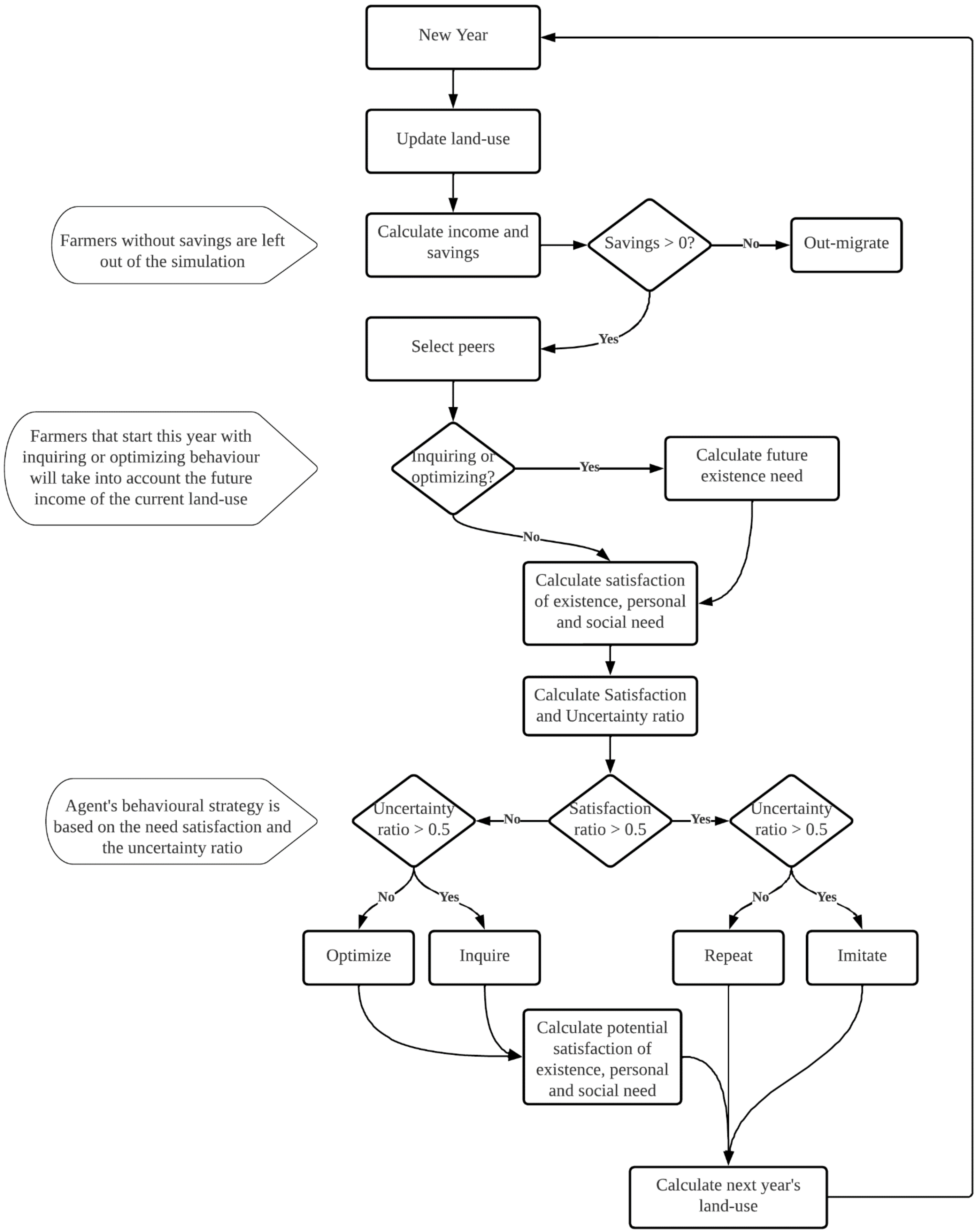

Figure 3.2.3a. *Overview of the order of processes, adapted from Speelman (2012, p. 128)*

The model can simulate different price trajectories for the crop prices: gradual increase/decrease, price shocks and permanent price increase/decrease. These values are derived from the global price data, and the values are embedded in the model code. The LUSES model does not use data from external sources.

3.2.4 Submodels

Sub-routines or submodels are the major processes of an ABM. For the LUSES model the most relevant of these are: income calculations (and cognitive function), peer selection, need satisfaction ratios and behavioural strategy selection.

Income calculation (and cognitive function)

The submodel of income calculation provides the annual income of selected land use types. The actual income of an agent is straightforward: based on the price of the land use type and the number of patches. The calculation of the expected future income is more intricate. To calculate this, the two main elements of this submodel are the past crop prices of each land use type and the cognitive function of agents. To calculate the expected future income, a linear function is used to predict the future income based on the prices of the last years.

Input:
- Land use prices;
- Past land use prices;
- Cognitive function.
Output:
- Annual income;
- Expected future income.
Used for:
- Expected income uncertainty;
- Potential income;
- Potential existence and overall need satisfaction;
- Existence need satisfaction*.

The number of years the price is memorized, is based in the value of the cognitive function (i.e. between 1 and 10). Agents are assigned a value for their cognitive function. This value is randomly chosen between 1 to 10 and indicates the number of years that a farmer remembers crop prices. The expected future income influences the expected income uncertainty, the potential income and the potential existence and overall need satisfaction. The expected future income also influences the existence need satisfaction of agents engaging with optimizing or inquiring behaviour. In addition to this, agent's uncertainty is influenced by the expected future prices of the agent's peers.

In the Consumat framework, agents have a mental map which allows them to remember past prices, choices or behaviours (of their own and others). The Consumat framework, however, does not specify the *amount* of time an agent will remember. For the LUSES model, agents are able to remember properties up to ten time steps (years), depending on the strength of their cognitive function. Associated with this is the decay-factor of the LUSES model: agents will forget properties after a certain amount of time steps.

Peer selection

This submodel covers the peers selection of 5 peers for each agent. These peers are selected on basis of five factors: land use selection, land use preference, savings, land holdings and distance. The statistics of the peers are used in multiple places in the model. For example, to calculate the uncertainty, the agent determines the uncertainty of the chosen land use type by comparing with the land use choices of peers, as well as looking at the expected future prices estimated by peers. The peers' statistics are also used to calculate the social need satisfaction, which is based on similarity (of land use) and superiority (regarding savings) of peers.

The peers statistics are also used for future predictions. To calculate the expected income uncertainty, the expected future income of peers is used. For the calculation of the potential social need satisfaction, peers land use choices are used.

Input:
- Agent's land use selection;
- Agent's land use preference;
- Agent's savings;
- Agent's land holdings;
- Distance between agents.
Output:
- Peers selection;
Used for:
- Expected income of peers;
- Similarity to peers;
- Potential social need satisfaction;

In the Consumat model, the mechanics of relationships with other agents are similar to the LUSES model. Other agents influence the outcome of the socially determined behavioural strategies (imitating and inquiring). The added sub-type of social need satisfaction introduces a new role for agent relationships into the model. In addition to this, the Consumat model does not specify a group of peers, i.e. there is no distinction in closeness or knowledge between different agents. The LUSES model does include a distinction between peers and the rest of the agents, thus allowing for the incorporation of social networks into the model.

Need satisfaction

Multiple submodels are used to calculate the overall need satisfaction. It is based on the social, personal and existence need satisfaction and the relative importance of each type of need satisfaction.

Social need satisfaction is calculated based on the similarity (of land use) and superiority (regarding savings) compared with peers. *Personal need satisfaction* is calculated by comparing the currently selected land use type with the land use type that is preferred by the agent. *Existence need satisfaction* is calculated based on the household needs and the income generated by the chosen land use type. Optimizing and inquiring behaviour also considers the expected future profit from the currently selected crop.

The social, personal and existence need satisfaction combined provide the overall need satisfaction. The weight of each sub-type of need satisfaction on the overall need satisfaction depends on the relative importance of each type. The overall need satisfaction is used to determine if the agent is or is not satisfied, which happens by comparing the agent's aspiration level with the overall need satisfaction. This forms the need satisfaction ratio. The choice of a behavioural option is based on the need satisfaction ratio and the uncertainty ratio.

Input:
- Existence need satisfaction;
- Social need satisfaction;
- Personal need satisfaction;
- Need satisfaction ratio;
- Aspiration;
- Uncertainty.
Output:
- Overall need satisfaction.
Used for:
- Need satisfaction ratio;
- Behavioural option.

The Consumat framework does not distinguish between different types of need satisfaction. The LUSES model does take this into account, distinguishing between existential, social and personal need satisfaction.

Uncertainty

Uncertainty is determined by looking at peer's expectations of future prices and peer's similarity of land use choices compared with the current year's land use choice. The *uncertainty ratio* checks whether the experienced uncertainty is higher than the agent's uncertainty tolerance level. This is used in the choice of the behavioural strategy.

Input:
- Expectations of future prices;
- Similarity.
Output:
- Uncertainty ratio.
Used for:
- Behavioural strategy selection.

Behavioural strategy selection

One of the four behavioural options is chosen. The behavioural options are: repeat, imitate, inquire and optimize. The choice for a behavioural option depends on outputs from two other submodels: the need satisfaction ratio and the uncertainty ratio. The selection of the behavioural strategy of the LUSES model is equal to that in the Consumat Framework and is shown in Figure 3.2.4. The behavioural strategies impact the choice of a land use type in the following manner:

To *repeat* means the land use choice of this year will be repeated. *Imitate* means the land use choice of next year will be based on the land use choice of this year of one of the peers. *Inquire* means the potential social, personal, existence and overall need satisfaction will be evaluated and the land use with the highest potential satisfaction will be chosen. The potential social, personal, existence and overall need satisfaction is calculated by evaluating agents' land use selection. *Optimize* means the potential social, personal, existence and overall need satisfaction will be evaluated and the land use with the highest potential satisfaction will be chosen. The potential social, personal, existence and overall need satisfaction is calculated by evaluating all land use options.

Input:
- Need satisfaction ratio;
- Uncertainty ratio.
Output:
- Behavioural strategy selection.
Used for:
- Land use choice.

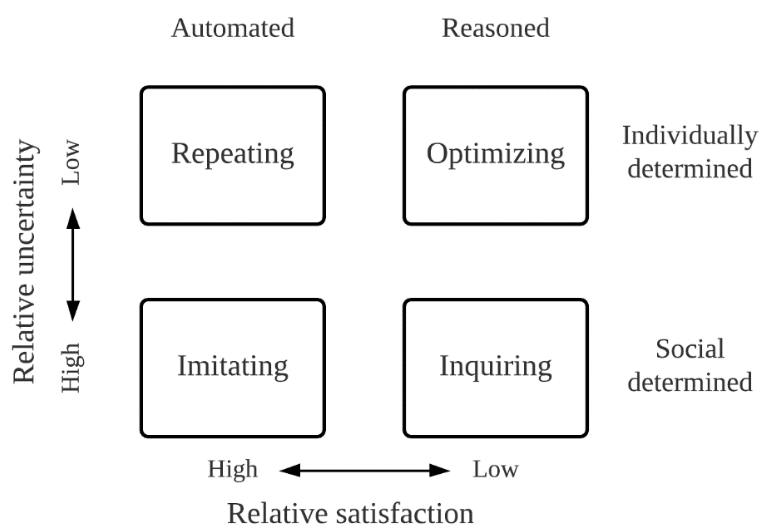

Figure 3.2.4. *The four behavioural strategies in relation to uncertainty, satisfaction, and concepts from* theory (copy from figure 2.3.3).

4 Methodology

In the second chapter, this research was placed within the context of literature on ABMs, the modelling of land use and the Consumat framework. In addition to this, the TyL study and the LUSES model were discussed extensively in chapter 3. The methods that are used to answer the research questions of this thesis are discussed in this chapter.

4.1 Research aim and research questions

As mentioned in the introductory chapter, the aim of this thesis is *to provide a quantitative evaluation of the robustness of the model parameters and the system assumptions of the LUSES-model, with special attention to the implementation of the Consumat framework.*

The sensitivity analysis (SA) is used as the main method to achieve this aim. Sensitivity analyses are used to validate the model output. Two different types of sensitivity analyses are distinguished by De Smith et al. (2018): sensitivity analyses that assess the model robustness, and sensitivity analyses that determine the effect of changes in the model assumptions on the model output. Both

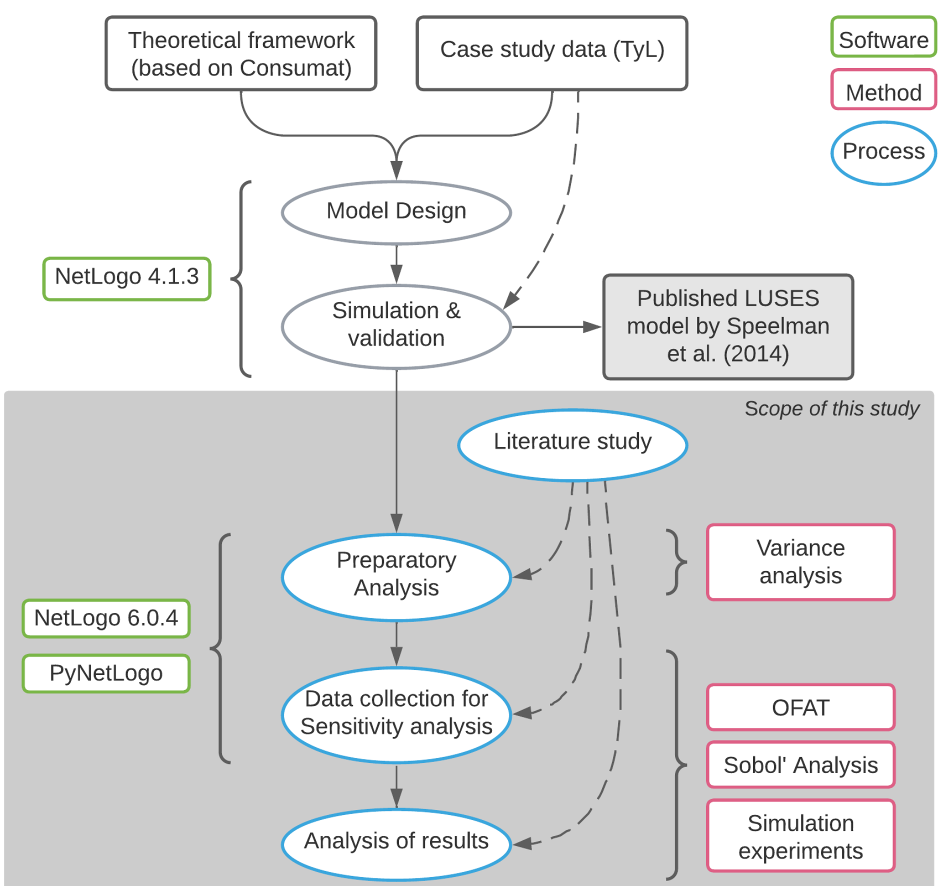

Figure 4.1 *Research design*

types of sensitivity analysis are used in this research. However, the total scope of the research does not just include (quantitative) sensitivity analyses. A literature overview was provided of the most important concepts related to ABM evaluations, and in addition to this the necessary adaptations and preparatory analysis for the sensitivity analyses were documented. Therefore, for this research a mixed-methods approach was used to provide a quantitative evaluation of the model parameters of the LUSES model. Since the research process is ordered similar to the research questions, the following section will describe the research design structured according to the four research questions.

4.2 RQ1: Discussing concepts for quantitative evaluation

The first research question (what are the most important concepts to understand a quantitative evaluation of the LUSES model?) was answered by means of a literature study, exploring the concepts of validation, verification, and sensitivity analysis for ABM evaluation. A snowballing approach was used, starting with research on verification and validation of ABMs by David, Fachada and Rosa (2017) and De Smith, Goodchild and Longley (2018), and research on sensitivity analysis by Ten Broeke, Van Voorn and Ligtenberg (2014). This discussion of literature created a strong theoretical groundwork for answering the other research questions, and was necessary since these concepts are often referred to in AMB research papers, but are not as often clearly defined.

4.3 RQ2: Adapting the model for quantitative evaluation

This research question (how to adapt the LUSES model to perform a quantitative evaluation?) is focused on the steps that were necessary to be able to execute the sensitivity analyses. Before the analyses could be performed, three steps were necessary: (1) to write a (Python) script for data extraction, (2) to adapt the LUSES model to accommodate the extraction of data, and (3) to perform a variance analysis on the LUSES model. This last step is an analysis focussed on finding the minimum amount of iterations needed to get stable model output. Because of the use of randomization, the model output of ABMs is (slightly) different for each simulation run. By taking the average value of a certain amount of runs, this variance of the model output is negated. The specific amount of runs needed to stabilize the model output is calculated by a variance analysis.

The second research question consisted of an approach where an iterative process of trial and error was combined with study of (1) academic texts on variance analysis, (2) source materials for the NetLogo program, and (3) source materials for the Python libraries.

4.4 RQ3: Assessing the robustness of the model parameters

The third and fourth research question were answered by means of sensitivity analyses which provided quantitative results, which were described in a mostly qualitative manner. The data that was used for research questions 3 and 4, was generated by iterating simulations of the LUSES model, using different parameter values for each analysis. The original LUSES model was provided by E. Speelman and was adapted to allow the gathering of data for the three different sensitivity analysis through a python script. The data that is used in the LUSES model, for example data on the crop prices, is embedded in the code of the LUSES model. This data originally was generated for a case-study conducted by E. Speelman, as discussed in chapter 3.

To clarify the discussion of the methods that were employed, the following distinction is made within this research. A single run of the LUSES model is referred to as one iteration or one model run. The average of multiple runs that are using the same parameter values, is referred to as the scenario output. For example a sensitivity analysis provides a comparison of 10 scenarios, each using a different value for the Cognitive effort parameter. The scenario that uses the baseline parameter settings is referred to as the baseline scenario. The output of multiple scenarios that use different values of the same parameter are referred to as an experiment. For example, for the system analysis experiment of cognitive function, 5 scenarios were compared (including the baseline scenario).

For research question 3 (how to assess the robustness of the model output due to parameter settings and their interactions?) two different methods of sensitivity analysis were used. First, the model's six main parameters were assessed by performing a one-factor-at-a-time (OFAT) sensitivity analysis for the exploration of the parameter ranges. This means experiments were conducted to detect the sensitivity of the model output to *individual* parameter changes. For each group of experiments, one parameter was assessed by changing the parameter value to a set value within the model's parameter bounds. This created an overview of the sensitivity of the model output to values of the model's six main parameters.

Second, for further exploration of the model dynamics, a global variance analysis was performed. This is similar to the OFAT analysis, providing insight into the influence of a parameter on the model output. The added strength of a global variance analysis is the exploration of effects of *interaction* between parameters. By using the Sobol's analysis, the sensitivity of the model's main parameters on the model output was explored with a focus on interaction effects (though the analysis does not provide insight into the robustness of the interaction effects). The analysis of interaction effects is especially important for ABMs of complex systems, since these models often have many ways parameters can influence each other: multiple interactions, and systems of feedback or learning (An, 2012).

4.4.1 Baseline settings and parameter values

Table 4.4.1a *Baseline settings of the model*

Price trajectories	TyL
Land division	TyL
Farmer's household size	5
Existence need of an individual	1.1
Farmer's starting savings	125
Collaborative threshold	0.33
Decay function memory	-1

In Table 4.4.1a the baseline settings of the model are shown. The analyses were ran using the baseline settings of the original LUSES study, i.e. both the price trajectories and the land division are set to values based on the TyL data. In addition to this there are set values for household size, existence need and starting savings. The collaborative threshold is set to 0.33, this indicates the amount of land that should be collaboratively managed before there will be collaborative benefits (higher crop prices). The decay function indicates each year the agents will forget the crop prices of one year (the one that is the longest ago). The model runs for 50 time steps.

Table 4.4.1b

Parameters used in analyses	*Baseline value*
Farmer's aspiration level	random, between 0.0001 - 1
Farmer's uncertainty tolerance level	random, between 0.0001 - 1
Farmer's cognitive effort*	random, between 1 - 10 years
Relative Existence need	between 0.8 - 0.99
Relative Social need	between 0.005 - 0.1
Relative Personal need	between 0.005 - 0.1

* *The farmer's cognitive effort is not used for the Sobol' analysis*

Table 4.4.1b shows the parameters that were used in the LUSES model with corresponding baseline values. For the aspiration level, uncertainty tolerance level and cognitive effort, the parameter value is randomly determined within certain bounds. The parameter values of the existence, personal and social need are relative to each other, adding up to 1. The existence need parameter values are relatively high, this value is randomly determined between 0.8 and 0.99. The values of the social and personal needs are calculated by the formula: *(1 - value existence need) / 2.* Therefore, the values of the social and personal needs are equal and range between 0.005 to 0.1. In the OFAT analysis and the Sobol' analysis the focus is on varying these values within the variable bounds.

4.4.2 OFAT Analysis

For ABM sensitivity analysis it is important to keep in mind the hardware requirements of the model analysis when selecting a particular method: complex models combined with complex analyses can cause high computational costs. The One-factor-at-a-time (OFAT) sensitivity analysis is a common local method with low computational costs. It is a very suitable starting point for an exploration of the model dynamics. The downside of the use of a local method such as an OFAT analysis is that it does not show interaction effects (Ten Broeke et al., 2016; Ten Broeke et al., 2014). Therefore, the OFAT analysis is chosen as a first, exploratory analysis, and an additional global SA is performed to further explore the robustness and check for interaction effects.

Table 4.4.2 *OFAT experiment values for each factor.*

	Aspiration	Uncertainty tolerance	Cognitive effort	Existence need	Social need	Personal need
1	0.0001 - 1	0.0001 - 1	1-10	0.8 - 0.99	0.005 – 0.01	0.005 – 0.1
2	0.0001	0.0001	1	0.80	0.005	0.005
3	0.1	0.1	2	0.85	0.025	0.025
4	0.2	0.2	3	0.90	0.050	0.050
5	0.3	0.3	4	0.95	0.075	0.075
6	0.4	0.4	5	0.99	0.100	0.100
7	0.5	0.5	6	-	-	-
8	0.6	0.6	7	-	-	-
9	0.7	0.7	8	-	-	-
10	0.8	0.8	9	-	-	-
11	0.9	0.9	10	-	-	-
12	0.9999	0.9999	-	-	-	-

Table 4.4.2 shows the values that were used for the OFAT experiments. For each factor specified below, the parameter value was set to a specific value (while keeping all other parameters at the baseline value). The resolution of the parameter variation (the incremental parameter change) was between 0.1 and 0.05, depending on the variable. The range of the parameter variation was between the minimum and maximum bounds of the parameter. For the need satisfaction experiments, the change of one parameter value meant the parameter values of all three need parameters no longer added up to 1 (the total value could vary between 0.81 and 1.19).

To illustrate the OFAT experiment values depicted in table 4.4.2, 11 experiments were conducted for the factor 'cognitive effort', which were run 200 times each. The first experiment is the baseline scenario, where the value of farmer's cognitive effort parameter is randomly determined between 1 and 10. For the next 10 experiments, all farmer's cognitive effort was set to the indicated values.

4.4.3 Sobol' analysis

There are three main methods for global sensitivity analysis: regression sensitivity analysis, model free methods like the Sobol' method and the surrogate model analysis (further discussed in the literature study of RQ1). Surrogate model analysis use machine learning techniques, but needs a high number of test and training data which are not available for the LUSES model (Zhang et al., 2020; Ten Broeke et al., 2021). Regression-based models use a regression function of the input parameters to explain the variance of ABM outcomes, and only work if there is a model fit (Ten Broeke et al., 2016). This often proves difficult for ABMs because of the high complexity. To avoid high computational costs because of a bad model fit of the regression-based method, and the subsequent necessity to perform an additional model-free analysis, this study does not use a regression-based model. Therefore, between these three types of sensitivity analysis, the model free methods like the Sobol' method seem the most suitable, the only drawback being this method does not provide insight into the robustness of interaction effects (Lee et al., 2015; Ten Broeke et al., 2016; Ten Broeke et al., 2021). A combination of OFAT and Sobol' analysis would therefore mean the analysis of the robustness of interaction effects is left out of the analysis (Ten Broeke et al., 2016).

The Sobol' analysis is a commonly used variance-based global sensitivity analysis method. These methods perform more complex assessments of parameter sensitivity (including interactions) compared with e.g. OFAT analyses, thus resulting in higher computational costs

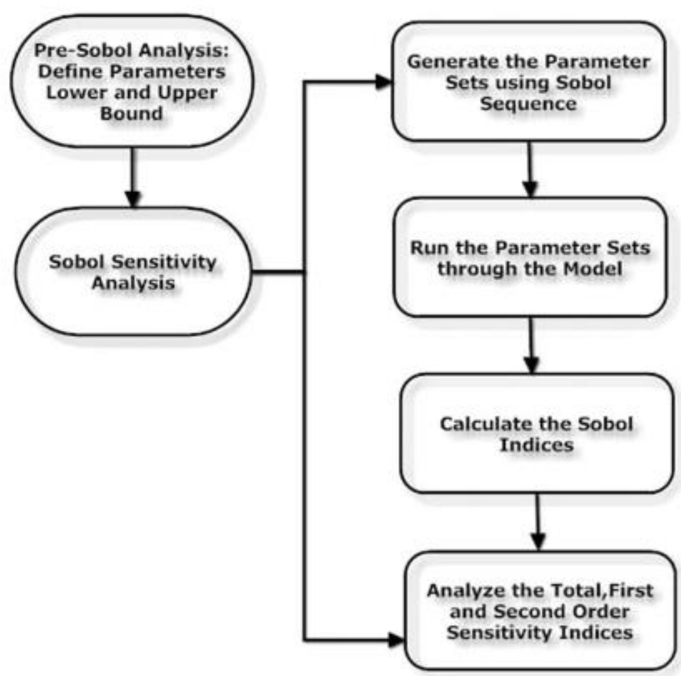

Figure 4.4.3a *Flow chart of the Sobol' analysis, from Zhang et al., 2015, p.72.*

(Zhang et al., 2015; Sobol', 2001). This kind of analysis can be used to rank the importance of input factors based on their contribution to the output variance. The Sobol' method measures indices for each parameter, but does not analyse the *robustness* of interaction effects. The Sobol' analysis allows for the quantitative ranking of variables in terms of the influence on the model output variance (Zhang et al., 2015).

It is customary to use the first order and the total effect Sobol' index, though there are other, higher order indices (Saltelli et al., 2010). The first order Sobol' index, expressed as S, estimates the direct contribution of a parameter to the total variance of a model, *without* interaction effects. A large contribution means the model is highly sensitive to changes in of the parameter. The first order Sobol' index allows for the ranking of influential parameters. The total effect Sobol' index, expressed as S_{Ti}, gives the measure of the total contribution of a parameter to the variance, *including* interaction.

Table 4.4.3b	Parameters used in Sobol' analysis	Baseline value
	Farmer's aspiration level	random, between 0.0001 - 1
	Farmer's uncertainty tolerance level	random, between 0.0001 - 1
	Relative Existence need	between 0.8 - 0.99
	Relative Social need	between 0.005 - 0.1
	Relative Personal need	between 0.005 - 0.1

The Sobol' analysis uses the same parameters as the OFAT analysis, with exception for the *'farmer's cognitive effort*' parameter. The Sobol' analysis uses continuous variables, and this parameter is a discrete variable, the numbers indicating years. One solution to this could be using a continuous variable in the Sobol' problem, rounding the numbers in NetLogo code. However, this causes inaccuracies between the Sobol' parameter values and the model outcome. This analysis could have been performed as a means of comparisons between the results of a Sobol' analysis with and without the Cognitive variable, however because of time constraints the running of an additional analysis was not possible. Because of this, the main Sobol' analysis does not include the cognitive variable.

4.5 RQ4: Examining the system assumptions

For the fourth research question (what impact can be expected by change of 'system' assumptions?), simulation experiments were run for three different scenarios. The analysis script that was used for the OFAT analysis is also used for the Systems Analysis (SysA). The method is similar to the simulation experiments in the LUSES study. Certain system assumptions will be qualitatively validated by running scenarios. These specific assumptions were selected because they are at the core of the Consumat model, especially the cognitive function and the need satisfaction ratios. In addition to this, the peer networks were an important part of the research of Acosta-Michlik and Espaldon (2008), which was very similar to the LUSES study. It is also advised by An (2012) to pay close attention to the impact of social networks on decision-making in psychosocial/cognitive models. The base settings of the models will be adjusted for each scenario, and the trends in the model outcomes and the variation in outcomes will be compared to the baseline scenario.

The following subjects will be covered in the scenarios of the SysA:

1. Cognitive function (memory decay and length of memory),
2. Peer networks (network sizes and weights of peer selection),
3. Social, personal and existence need satisfaction ratios.

This analysis differs from the OFAT analysis in that it either assesses the variation of non-baseline variables (for the cognitive function and the peer network experiments) or because it changes multiple baseline parameters simultaneously and outside the parameter bounds (for the need satisfaction experiments). In addition to this, the aim of the system analysis is to examine the system assumptions while the aim of the OFAT analysis is to assess the robustness of parameters.

4.5.1 Cognitive function

In the baseline scenario, the Farmer's cognitive effort is determined randomly with a value between 1-10 years. The decay function is -1, meaning each new year farmers forget the prices of the year that is the longest ago. In this scenario different alternatives will be explored. These are:

- No decay of memory
- Strong cognitive function (15, 20, 25 and 30 years)

Table 4.5.1	Cognitive effort	Memory
	Experiment 1*	1-10 years
	Experiment 2	1-15 years
	Experiment 3	1-20 years
	Experiment 4	1-25 years
	Experiment 5	1-30 years
		Decay
	Experiment 1*	-1
	Experiment 2	0

The first scenario explores the model output when agents have no decay of memory: they do not forget any prices. This is the way the Consumat framework is modelled, so it allows for the exploration of this difference between the LUSES and the Consumat framework. The second scenario explores some more extreme values of the cognitive function. This parameter is also assessed by the OFAT analysis, which looks at agents remembering 1 to 10 years. This scenario will explore agents remembering 15, 20, 25 and 30 years.

4.5.2 Peer networks

In the original LUSES model, agents can choose up to 5 peers. These peers are selected based on the similarity of 1) land use selection, 2) land use preference, 3) savings, 4) land holdings, 5) relative distance to peer (X coordinates), and 6) relative distance to peer (Y coordinates). In the baseline scenario these six factors have equal weight in the selection of peers. The exploration of the subroutine of peer selection was executed in two parts. First, the influence of the *number* of peers was explored by comparison of the scenario's shown in Table 4.5.2a.

Table 4.5.2a	Number of peers	nr_peers variable
	Experiment 1	1 peer
	Experiment 2*	5 peers
	Experiment 3	10 peers
	Experiment 4	20 peers
	Experiment 5	30 peers

* *Baseline scenario*

The second part of the exploration of the peer networks is to apply different weights to the peer's selection criteria. Specifically, this assessed the importance of geographical location, and the influence this has on the model output. This was achieved by assigning weight ***a*** to the non-distance selection criteria (land use selection, land use preference, savings and land holdings), and assigning weight ***b*** to the distance selection criteria (X coordinates, Y coordinates). The combined weights add up to 6. See Table 4.5.2b for the weights of each experiment. This resulted in the following scenario's:

Table 4.5.2b	Weighted peer selection	*Weight a*	*Weight b*
	Experiment 1	0.00	3.00
	Experiment 2	0.25	2.50
	Experiment 3	0.50	2.00
	Experiment 4	0.75	1.50
	Experiment 5*	1.00	1.00
	Experiment 6	1.25	0.50
	Experiment 7	1.50	0.00

* *Baseline scenario*

4.5.3 Need satisfaction ratios

The ratios of the relative existence, social and personal need satisfaction (as shown in the OFAT section) have already been assessed in the original LUSES study, where the high existence need ratio

(0.8-0.99 existence need satisfaction, 0.01-0.1 social need satisfaction and 0.01-0.1 personal need satisfaction) showed significantly more similarity to the empirical data compared with the equal need importance ratio (0.33 existence need satisfaction, 0.33 social need satisfaction and 0.33 personal need satisfaction). In the OFAT analysis the need satisfaction ratio is be assessed within the bounds of the high existence need ratio. In this secondary analysis other scenario's will be explored, focussing on the ratio between the existence, social and personal need satisfaction.

The selected scenarios are depicted in Table 4.5.3. The first scenario is the baseline scenario. The scenarios 2 and 3 explore a (relatively) high existence need (0.6) with either a low social need (0.3) and a very low personal need (0.1), or a very low social need (0.1) and a low personal need (0.3). Scenarios 4 and 5 explore either moderate existence and social need (0.45) and very low personal need (0.1), or moderate existence and personal need (0.45) and very low social need (0.1). Scenarios 6, 7 and 8 explore a very low existence need (0.1) with either moderate social and personal need (0.45), high social need and low personal need (0.6 / 0.3) or low social need and high personal need (0.3 / 0.6).

Table 4.5.3		*Existence*	*Social*	*Personal*
	Experiment 1 (baseline)	0.8-0.99	0.01-0.1	0.01-0.1
	Experiment 2 (high existence)	0.6	0.3	0.1
	Experiment 3 (high existence)	0.6	0.1	0.3
	Experiment 4 (moderate existence)	0.45	0.45	0.10
	Experiment 5 (moderate existence)	0.45	0.10	0.45
	Experiment 6 (low existence)	0.1	0.45	0.45
	Experiment 7 (low existence)	0.1	0.6	0.3
	Experiment 8 (low existence)	0.1	0.3	0.6

5 Results

The result chapter is structured according to the four research questions. Section 5.1 discusses the most important concepts for evaluation of ABMs. In section 5.2 the preparatory analysis and the model adaptations are discussed. The results of the sensitivity analyses are discussed in section 5.3 and 5.4, where the robustness of the parameters (assessed by the OFAT and Sobol' analysis) is covered in section 5.3, and the impact of changes of specific system assumptions (assessed by simulations) is discussed in section 5.4.

5.1 RQ1: concepts for quantitative evaluation

In the next section, an answer to the following question is provided: "what are the most important concepts to understand a more quantitative evaluation of the LUSES model?". A distinction between validation and verification is made in 5.1.1. Next, in section 5.1.2 a conceptual framework is used to explain the process of validation and verification for computational models. After this, section 5.1.3 discusses the four different types of validation/verification in depth. Section 5.1.4 provides more context to the use of sensitivity analysis (SA). After this general introduction, the main types of SA will be discussed in section 5.1.5, providing a more extensive background to the discussion of the SA in the methodology chapter.

5.1.1 Defining validation and verification

Within the literature on the validation of computational models (such as ABMs) the concepts of verification and validation are closely related, and even overlap according to some definitions. As these concepts are often referred to in AMB research papers, but are not as often clearly defined, it is important to define both concepts, and to draw the distinction between the two (Ngo & See, 2012; David et al., 2017). Broadly speaking, the difference between verification and validation lies in the subjects of inquiry. The aim of the process of verification is to check whether the *model* functions properly (and corresponds to the conceptual model), while the aim of the process of validation is to assess whether the model output approaches the *phenomenon* close enough (Wilensky & Rand, 2015; David et al., 2017). Operationally, the concepts are used interchangeably, for example in the case of internal validation and the verification of model output, which are discussed in section 2.4.3.

In their work, both Ngo and See (2012) and David et al. (2017) describe the scientific debate concerning the conceptualization and terminology of validation. The concept of validity is inherited from statistical research and has been defined in statistics as "*a comparison of the model's* *predictions with the real world to determine whether the model is suitable for its intended purpose*" (Mayer & Butler, 1993, p. 21). But within the realm of simulations these concepts are in a pragmatic sense more related to software engineering (David et al., 2017). Different model aims, and subsequent methodologies call for different validation methods, tests, and techniques (David et al., 2017).

The operational definition of validity therefore depends on the context of the model (i.e. its intended purpose). About the aim of the LUSES model, Speelman writes: "*The LUSES [...] agent-based model aims to explore land use dynamics in agricultural landscapes through the implementation of the conceptual update of the social-psychological CONSUMAT mode*l" (2014, p. 126). Therefore, at its core the LUSES model is an explorative model. For sake of brevity, the following section will focus on the discussion of validation and verification methods and techniques that fit this aim.

5.1.2 A conceptual approach to validation and verification

Figure 5.1.2 shows a visual representation of the role of verification and validation in the ABM developing process. This figure, adapted from the research of David et al. (2017, p.175), will be used to explain validation and verification of ABMs.

On the left, the 'pre-computational model' indicates the conceptual ABM as researchers envision it. On the left top, there is a process of model validation (1) in comparing the conceptual model with the theory or phenomenon. On the bottom, the 'executable computational model' indicates the conceptual ABM, programmed as a working ABM model. There is a process of model verification (2) in ensuring the executable model is in line with the conceptual ABM.

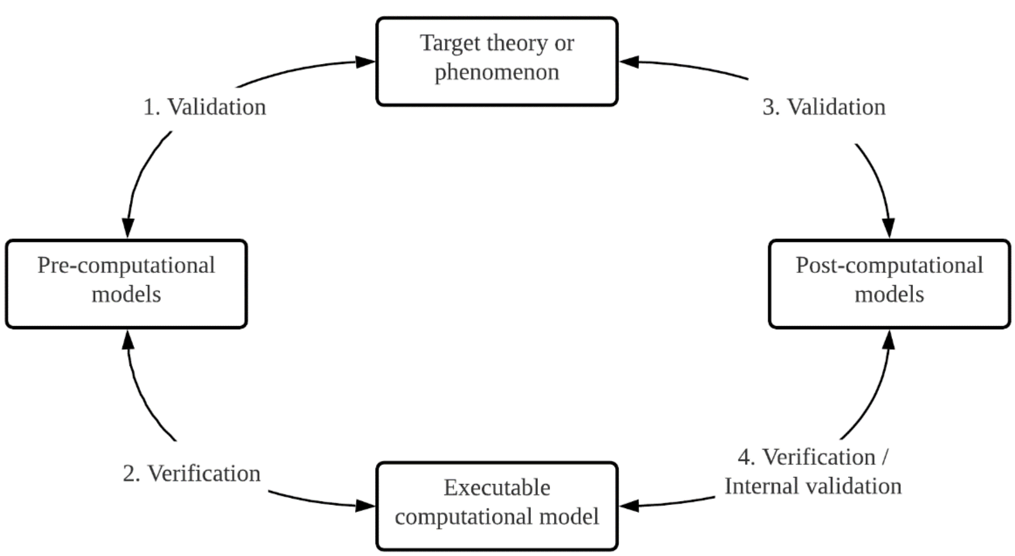

Figure 5.1.2. *The role of verification and validation in the development process of ABM's (adapted from David et al., 2017, p. 175).*

By analysing and describing the output of the executable model, a conceptual model of the analysis output can be drafted. These are indicated on the right, as 'post-computational models'. If emergent processes were discovered when analysing the model output, new categories of descriptions can be added to the post-computational model. The same process of validation takes place, this time comparing the post-computational model with the theory and/or phenomenon (3). There also is a similar process of verification of the model output (4), by checking whether the simulation results are correct on a functional level. This type of verification (verification of the model output) is commonly referred to as *internal validation* (David et al., 2017). These four types of validation/verification are further discussed in section 5.1.3.

It should be noted that the process of validation and verification, though presented as a numbered sequence, are not necessarily executed in a strictly chronological order. The development of a computational model is iterative, for example there might be a need to revisit the validation or verification process on the left if there is an unexpected or unexplained outcome of the model. In addition to this, it is important to note that though a model can work perfectly according to the intentions of the researcher and can be verified, the theoretical groundwork of the model can be faulty and therefore the validation will not be successful.

De Smith et al. (2018) also provide a dissemination of the validation process. De Smith et al. (2018) describe the validation process in three steps: (1) internal validation, (2) model calibration, and (3) validation of the model output. Thus they distinguish two kinds of validation: validation of the model output, and internal validation (which aims at uncovering whether the model behaves as expected). Comparing this with the work of David et al. (2017), the validation process as discussed by De Smith et al., overlaps with what David et al. define as the verification and validation of the model output (the right side of figure 5.1.2). The calibration of the model overlaps partly with the processes of pre-computational model verification and validation, as shown on the left in figure 5.1.2.

This illustrates how the verification of the model output if often referred to as '*internal validation*'. Other uses of the term internal validation can be found, for example, in the work of Mayer and Butler (1993) and Ngo and See (2012). This illustrates the confusing indication of different methodological concepts, but also shows the use of the concept 'internal validation' is common and well understood. Therefore, in the next section the terminology adheres to the distinction of the validation process as provided by David et al. (2017), aside from the model output verification which is referred to as internal validation.

5.1.3 The processes of validation and verification

The discussion of the processes of verification and validation is covered in the next section, and is divided into the following sub-sections: 1) model validation, 2) model verification, 3) validation of the model output, and 4) internal validation (verification of model output). The numbers of the sections adhere to the numbered processes in figure 5.1.2. Within this section the technique of the sensitivity analysis will be placed into a broader methodological context.

1. *Model validation*

This first process of model validation is described by David et al. (2017) to take place during the process of conceptualization and construction of the pre-conceptual model. The target theory or knowledge of the phenomenon is translated into computational rules and code. This initial process of model validation is not covered within this research. For this study it is assumed the theory and phenomenon are translated into the conceptual model as the researchers intended.

2. *Model verification*

The process of model verification looks at the question whether the conceptual (or pre-computational) model has been implemented adequately in the executable computational model. The two main ways to verify a model according to David et al. (2017) are (1) by using traces and (2) by structured walk-throughs. When using traces, a model variable is followed throughout a simulation in order to check whether the logic and precision is correct. The use of structured walk-throughs means the model code is checked statement by statement in a group setting (David et al., 2017).

For the verification of models that are built from scratch (i.e. using a general programming language), one should be mindful of the importance of testing and debugging in terms of programming practices (De Smith et al., 2018). However, for cases where models are built with modelling toolkits such as NetLogo, David et al. state: *"verification mainly consists of guaranteeing that the model has been correctly implemented"* (2017, p. 177). De Smith et al. (2018) dispute this and state "*the most thorough way of verifying a model is to re-implement the model using a different programming language and ideally a different ABM toolkit*" (2018, p. 517). This can also be found in the work of Edmonds and Hales (2005), who state the only way to be sure the theory can be trusted is if the model has been properly replicated and the results remain stable. But this is not always feasible in terms of time and resources, and an alternative is to provide an extensive model description to allow for replication and comparison of ABMs (De Smith et al., 2018). This however can be difficult in terms of publication word limits and lack of a structured way to present model descriptions.

To improve this, protocols have been made which improve the documentation of simulations (De Smith et al., 2018). An example is the ODD (Overview, Design concepts and Details) protocols. The ODD protocol has been extended to the ODD + D protocol, in order to better capture human decision-making into model descriptions (Müller et al, 2013; Siebers et al., 2021). The LUSES model has been described according to the ODD protocol. Since the LUSES model has been verified for the study by Speelman (2014), it is assumed the conceptual model has been correctly implemented. Further model verification will therefore not be attempted in this study. In the next section the validation of the model output is discussed.

3. Validation of model output

The focus on the validation of the model output is on assessing whether the model outcomes are consistent with the theory and/or phenomenon. David et al. (2017) distinguish three main methodological perspectives for the assessment of the validity of a model: prediction, retrodiction and structural validity. A model can be validated by comparing the model outcomes with future observations (*prediction*) or past observations (*retrodiction*). Since the LUSES model is explanatory in nature, predictive validity is not relevant for this study. Retrodictive validity assumes that a consistent reproduction of a phenomena from the past indicates the model mechanics can be appropriate to explain the system. For this type of validation, the technique of *historic validity* can be used. This means the model outcomes are compared to historical data.

In the qualitative validation of the LUSES study, the simulation experiments have been compared with empirical data from the TyL case-study, to assess the explanatory power of the model. However, since the LUSES model is made for a specific context, the use of this technique is limited when used on its own. In addition to predictive or retrodictive validation of model outcomes, the model mechanics should be validated as well. This methodological perspective is referred to as *structural similarity*.

Structural similarity looks at the mechanics on the micro-level and the behavioural patterns at the macro-level of the model and compares this with the real-life phenomenon (both theory and empirical data). Two main techniques to assess structural validity are (1) validation of simulation output, and (2) solution space exploration. These are discussed next. Roughly these techniques can be described as relating to the assessment of the validity of the model output and the validity of the model itself, respectively.

To assess the *validity of simulation output*, the simulation is ran with different parametrisations, for example extreme parameters. This technique used to assess the validity of simulation output can also be used to assess the internal validity of the model. The output of these simulations with different parameters is checked and should be reasonable. This technique provides a general understanding of the influence of different parameters on the model output and model behaviour; however the model assumptions are not considered. The model assumptions consist of input parameters, the model structure, the submodels, and the relations between these elements. These model assumptions are varied in the *exploration of the solution space*.

The exploration of the solution space can be done by carefully designed experiments, or less structured by analysing scenarios. The goal is to gain a better understanding of the influence of input parameters on the model output. Scenarios can be used to tests assumptions on the conceptual level (e.g. submodels for decision processes or learning mechanisms) or on the system level (low-level elements). Especially for the design of experiments, there often is a clear objective in mind. For the exploration of the solution space, David et al. (2017) name four common objectives: optimisation, calibration, uncertainty analysis and sensitivity analysis.

Of these objectives the sensitivity analysis (SA) is the most common, though all objectives have the common goal: providing insight into the model by exploring parameter settings and the corresponding output (Lee et al, 2015). Lee et al. (2015) mention the SA being a particularly important exploration task. This will be further discussed in section 5.1.4.

Within the original LUSES study, the validation of the model output has been assessed by analysing model scenarios. A more extensive validation is however needed, both to carefully assess the validity of the simulation output, and to assess the model assumptions by exploring the solution space.

4. Internal validation

The focus of internal validation (i.e. verifying the model output) is on assessing whether the model output is consistent with the computational model; the model rules and assumptions. It checks whether the model works as intended. Analysing the internal validation can be done by testing hypotheses about the model outcomes, based on the conceptual design, on different parameter settings. This is complicated by two factors. The first is the difficulty in distinguishing between errors in the model logic and 'real' model outcomes (De Smith et al., 2018). As mentioned, complex systems can contain emergent processes, which are discovered in the model analysis. Since these results are unexpected this complicates the verification of model output (Sætra, 2017; David et al., 2018). The second difficulty is the randomization aspect which occurs in most ABMs, as random numbers (used to account for aspects that are unmeasurable or random) cause the model to produce different outcomes for each simulation (De Smith et al., 2018).

If there is no quantitative data available to test the model (which is the case for most social-psychological models), the model can be verified by assessing whether the model input and output meet the researchers' expectations and intentions for a pre-established parameter range (David et al., 2017, p. 177). The model output has been verified for the original LUSES study, however this could be analysed more extensively.

To summarize, according to David et al. (2017) validation checks whether the theory or the phenomenon is reflected appropriately in the model and the model outcomes, while verification checks whether the model functions as intended. They make a distinction between the validation/verification of the *model* and the *model output*. The four types of validation and verification were discussed, and the sensitivity analysis validation technique was placed into a broader methodological context. From this it can be concluded the focus of the LUSES study is mostly on the assessment of the validity of the model outcomes (which can be placed within the methodological perspective of structural validation) and on providing further internal validation. This includes assessing the validity of the model and the model output, e.g. by sensitivity analysis that explore different parametrisations or scenarios. The next section discusses the use of and different types of sensitivity analysis.

5.1.4 Why sensitivity analysis?

Ten Broeke et al. (2014) describe sensitivity analysis for ABM as "*a statistical tool to analyse the effects of variations and uncertainty in input on the resulting output*". The SA differs from the uncertainty analysis by a focus on the question 'what input is responsible for the variability in outcomes?', where the uncertainty analysis answers the question 'what is the variability of results?' (Lee et al, 2015). For explanatory ABMs, sensitivity analyses have two main aims: firstly, to assess whether the model is able to explain a certain phenomenon (by looking into patterns or emergent properties), and secondly to assess how robust the explanation is to parameter changes (Ten Broeke et al., 2021).

Choosing an efficient and relevant method of sensitivity analysis is very important when analysing ABMs. AMBs can hold a large number of parameters, strongly non-linear relations, and complex relations between inputs and output (Ten Broeke et al., 2014; Ten Broeke et al., 2021). Emergent properties and tipping points are part of the complex behavioural structures that can be modelled by ABMs. This level of complexity increases the hardware requirements and computational costs

(Zhang et al., 2020), limiting extensive explorations of the model parameters due to the often high number of parameters and the high computational costs for each model iteration (Ten Broeke et al., 2021).

This means a model's computational costs should be taken into account when choosing a certain method for the sensitivity analysis. As a rough categorization, models that have low computational costs have runs that take milliseconds to some minutes. These models are suitable for quantitative analysis. Models whose runs take tens of minutes to tens of hours have (very) high computational costs. These models should be analysed using qualitative methods (Saltelli, 2002). The LUSES model takes about 10-15 seconds to run for 50 timesteps. Therefore the quantitative sensitivity methods are suitable for this model. The use of methods that use (pseudo-)Monte Carlo sampling techniques (random sampling using probability) can lower the computational costs of an analysis (Saltelli et al., 2010).

Sensitivity analysis can provide insight into ways to improve the model. By testing the effect of different model assumptions or parameter values on the model output, the output variance can be reduced. In addition to this, the model accuracy can be improved or the model might be simplified, e.g. by taking out inconsequential parameters. The sensitivity analysis might also point out assumptions that need to be further specified in order to properly contribute to the model (Ligmann-Zielinska, 2018; Lee et al., 2015). These model improvements are provided by an assessment of the ability of the model to explain a phenomenon, and by assessing the robustness of this explanation to parameter changes.

5.1.5 Methods for sensitivity analysis

Ten Broeke et al. (2016, p. 14) mention three main aims of sensitivity analysis: to examine patterns, to examine robustness, and to quantify outcome variability due to parameters. Different techniques or methods of sensitivity analysis fit the different aims of sensitivity analysis. Broadly, there are two types of sensitivity analysis: local methods and global methods. Local methods assess one parameter at a time, where global methods change multiple parameters at a time (Wan et al., 2015).

The most common local method is the OFAT (One-factor-at-a-time) analysis. OFAT sensitivity analyses are very suitable to use as a starting point for ABM analysis. The OFAT analysis helps to better understand the model dynamics by indicating strong non-linearities and tipping points (Ten Broeke et al., 2016; Ten Broeke et al., 2014). The OFAT sensitivity analysis does not show interaction effects, therefore additional analysis is necessary to get a complete picture of the robustness (Ten Broeke et al., 2021). This method of sensitivity analysis is therefore a good starting point for a first exploration of the model dynamics and fits the aim of examining patterns. It also has smaller computational costs because of the lower complexity compared to global methods (Wan et al., 2015).

The global sensitivity methods are sensitivity analysis methods that also aim to identify the influence of parameters on the model output, however these methods do look at interaction effects (Saltelli, 2002). These methods draw model output samples from a broad range of parameter values, calculating the variance of model output. The sensitivity of a model to a certain parameter is defined by the amount of variance that is explained by changes in that parameter (Ten Broeke et al., 2016). A downside of the use of global variance-based sensitivity analyses are increased computational costs. Within literature, common types of global sensitivity analysis are variance based global methods such as regression-based sensitivity analysis or model-free methods of sensitivity analysis (such as Sobol' method), and the more recently added surrogate analysis method (Ten Broeke et al., 2016; Wan et al., 2015). These three types of global sensitivity analysis will be discussed next.

Both regression-based sensitivity analyses and model free methods like the Sobol' method can be used to quantify outcome variability. The use of these methods allows for the breaking down of the variance of different parameter combinations. Regression-based sensitivity analysis can be helpful to further examine the robustness of the model outcomes. This kind of global variance analysis uses a regression function of the input parameters to explain the variance of ABM outcomes (Ten Broeke et al., 2016, p.3). The most commonly used method for regression-based sensitivity analysis is the ordinary least squares (OLS) regression. For this method R^2 represents the explained variance (Ten Broeke et al., 2016). These methods can however only be used if there is a good model fit. This means most of the variance of the model outcomes should be explained by the regression function. Because of the complexity of ABM, this often proves to be difficult.

Variance based methods on the other hand are model free methods, often using Monte Carlo sampling to assess different parameter variations (Saltelli et al. 2010). The Sobel' method is an example of a model-free method, which means no assumptions are made about relations between input and output (Ten Broeke et al., 2014). By use of Monte Carlo (or quasi-Monte Carlo) sampling methods for complex models, the global sensitivity indices can be efficiently determined (Sobol', 2001). The indices of the Sobol' method provide a measures of the contribution of each parameter to the variance of the model output. The *first order indices* represent the direct contribution to the total variance, without interaction effects, while the *total effect indices* represent the contribution of the parameters including interaction effects. The Sobol' indices do not assess the robustness of interaction effects.

A third method that could be adopted is the surrogate model analysis. This type of sensitivity analysis makes use of machine learning techniques (Zhang et al., 2020; Ten Broeke et al., 2021). These models need a high number of test and training data, which is not available in the LUSES case.

Conclusion

This section aimed to answer the question: "what are the most important concepts to understand a more quantitative evaluation of the LUSES model?". The concepts of validation and verification were discussed and a distinction was made between the two concepts, drawing from different academic texts. Through the use of a conceptual framework, the process of verification and validation of ABMs was visualized. A distinction was made of four different types of validation/verification, and these types were discussed in depth. Two types of validation were found to be relevant for this research. The validation of model output, which means providing insight into the model by exploring parameter settings and the model output, and internal validation. This type of validation focusses on the exploring consistency of the model with the model rules and/or assumptions. Both types of validation can be assessed by the use of sensitivity analyses. Therefore, the concept of sensitivity analysis for ABMs was discussed and put into context. The main types of ABM sensitivity analysis were discussed, providing a more extensive background to the choice of this research's methods.

5.2 RQ2: Preparatory analysis

This section discusses the steps that were taken to prepare for the three sensitivity analyses. It provides an answer to the second research question: "how to adapt the LUSES model to perform a quantitative evaluation?". The three steps to prepare the LUSES model for analysis, as mentioned in the methodology chapter, are: (1) to write a (Python) script for data extraction, (2) to adapt the LUSES model to accommodate the extraction of data, and (3) to perform a variance analysis on the LUSES model. These steps were not executed in a chronologic manner: the writing of scripts, editing of the LUSES model and execution of the variance analysis was an iterative process. There were no detailed guidelines to make the link between NetLogo and Python, therefore this part of the research was a process of trial and error. The three steps are discussed more in depth in the following section.

5.2.1 Writing the Python scripts

To allow for easy data collection, the analyses were executed using Python scripts (in Jupyter Notebook). The Python package PyNetLogo (Jaxa-Rozen & Kwakkel, 2018) was used to create a link to the NetLogo interface from the Python script. Another notable Python package is the SAlib package (Herman & Usher, 2017), a Python package that provides common methods for sensitivity analysis. This package was used to access the functions for the Sobol' Analysis.

For the OFAT and SysA analysis, the Python scrips were used to extract the values of certain variables for each time step of a model iteration (for a total of 50 time steps). For each scenario the averages of 200 runs (as determined by variance analysis) were calculated for each time step. The differences between scenarios were visualized using the Matplotlib python library. The baseline scenario was used to normalize the results, the figures therefore indicate the percentage that a scenario deviates from the baseline scenario. For the Sobol' analysis the data collection used a different script. This was done using the SAlib library, by calling the function SALib.sample.saltelli.sample() and SALib.analyze.sobol.analyze(). This is further discussed in section 5.2.3 on the variance analysis of the Sobol' analysis. The results of the Sobol' analysis were also visualized using Matplotlib.

5.2.2 Adapting the LUSES model

NetLogo model changes

The original LUSES model was written in NetLogo version 4.1.3. For this thesis, the LUSES model was adapted to a newer version of NetLogo: version 6.0.4 (Wilensky, 1999). This specific version was chosen because it is the latest version that is compatible with some of the Python packages that were used for the data analysis.

To be able to retrieve data from the Python-NetLogo interface, a list of so-called 'reporters' were added to the NetLogo script. These reporters report the value of a certain variable for each time step. In addition to this, the code of some elements of the original LUSES model were rewritten to fix bugs and errors that occurred when running the analysis in NetLogo 6.0.4. Some parts of the model code were rewritten to allow for the input and extraction of values from the Python script. Specific elements that were changed to make the code work in NetLogo 6.0.4 (apart from general code updates), were the Tierra y Libertad land division function and a change to the calculations of averages (to improve running time).

There were also some changes or additions to the model to allow for input/extraction of values via the Python script. Apart from the addition of a list of reporters, variables for the systems assumptions needed to be added (to allow the user to specify the number of peers and weights to the peer selection). For the Sobol' analysis, input of floating numbers from the Python script was made possible by adding input buttons to the NetLogo interface. An additional change is the rewrite of the expected future income calculations (using cognitive code), to facilitate the analysis of the system assumptions. The implementations of each of these changes was analysed by comparing the model output with the baseline model: these changes did not impact the model logic or model outcomes.

Table 5.2.2. *List of the reporters that were added to the NetLogo model*

Table 5.2.2	*Reporter*	*Description*
	Land use 1	patches of land use 1 (individual, cleared field) / total patches
	Land use 2	patches of land use 2 (collaborative, cleared field) / total patches
	Land use 3	patches of land use 3 (individual, forest-based) / total patches
	Land use 4	patches of land use 4 (collaborative, forest-based) / total patches
	Cleared field	cleared field land use (land use 1 + land use 2) / total patches
	Forest cover	forest-based land use (land use 3 + land use 4) / total patches
	Individual	individual land use (land use 1 + land use 3) / total patches
	Collaborative	collaborative land use (land use 2 + land use 4) / total patches
	Repeat	farmers with repetitive behaviour / total farmers
	Imitate	farmers with imitate behaviour / total farmers
	Inquire	farmers with inquire behaviour / total farmers
	Optimise	farmers with optimize behaviour / total farmers
	Overall need	average overall need satisfaction of farmers
	Ex. need	average existence need satisfaction of farmers
	Social need	average social need satisfaction of farmers
	Personal need	average personal need satisfaction of farmers

NetLogo reporters

Within the NetLogo programming language, reporters can be used to report a variable value for each time step. Through the use of reporters, variable values could be extracted with the PyNetLogo link. Sixteen reporters have been added to the NetLogo script. These reporters are used to analyse the influence of parameter changes on the model outcomes. These reporters ensure the output of the model can be analysed by looking at the changes in land use choices, the changes in behaviour or the changes in the need satisfaction. These reporters are used for all three analyses. A description of all reporters is provided in Table 5.2.2.

5.2.3 Variance analysis

Variance of the OFAT analysis

The use of randomization in ABM's results in (slightly) different outputs for each simulation run (De Smith et al., 2018). Because of this, many runs of a model are needed to stabilize the output, increasing the time and resources needed for an analysis. The number of repetitions can be determined by assessing the number of runs needed to reach variance stability. Variance stability means the variance stays within certain pre-defined bounds of the sample mean. There are different metrics to measure variance stability, examples are the *confidence interval bound variance* and the

Table 5.2.3. *Variance analysis for the land use 1 reporter, with p-values p = 0.05* (*) *and p = 0.01* (**).

Nr. of runs	Avg. Exp 1	Avg. Exp 2	Difference
5	10486,82	10504,44	-17,6236
20	1120,435	1120,216	0,21869
50	200.9208	201.302	-0.38123
75	91.7131	91.80537	-0.09227
100	52.30217	52.31404	-0.01187*
125	33.76568	33.75195	0.01371*
150	23.56439	23.55562	0.008768**
175	17.37733	17.39137	-0.01405*
200	13.34171	13.3424	-0.0007**
225	10.56306	10.55899	0.004069**
250	8.570843	8.569458	0.001385**
275	7.094145	7.096718	-0.00257**
300	5.969734	5.970879	-0.00115**
325	5.094887	5.090587	0.0043**

coefficient of variation. Just like the standard error of the mean, these metrics will show a quite unstable variance for a small set of sample runs. The appropriate (or minimum) amount of runs for the analysis can be determined by comparing the confidence interval from runs of different sample sizes to find the point of stability (Lee et al., 2015).

To determine the appropriate amount of runs for this research, the variance of the *variance of each time step* was assessed. The variance was calculated for each reporter, since a proper sample size is needed for *all* model outputs in order to perform a reliable analysis (Lee et al., 2015, p.5). This variance analysis was performed by running experiments with the same base settings for an alternated number of repetitions, as can be seen in table 5.2.3.

Experiments were performed with a number of 5, 20, and 50 to 325 runs with 25 runs increments. Each experiment was repeated twice to allow for comparison. During these runs the model output of the reporters was saved for each time step. For the gathered data, first the variance of each time step was calculated. Secondly, the variance of the variance of each timestep was calculated, resulting in the values shown in figure 5.2.3. This figure shows the variance stabilized around 100 runs, and a stable p-value of 0.01 was reached after 200 runs. This was similar for the other reporters. Therefore a sample size of 200 was selected for the OFAT experiments.

Variance of the Sobol' analysis

The sample size for the Sobol' analysis differs from the regular determination of the sample size. The SALib Sobol' analysis can be divided into two parts. The generation of model inputs (the sampling scheme) is generated by the function "SALib.sample.saltelli.sample()". This function uses the Sobol' sequence as extended by Saltelli, which reduces the error rates of the sensitivity analysis. The function "SALib.analyze.sobol.analyze()" performs the Sobol' analysis on the model output. The output of this function are the indices (first and total order) and the corresponding confidence levels (SALib, 2021). The values of the confidence bounds indicate the probability of the given value of the indices. The alpha value of P = 0.05 will be used in this analysis.

The function for the sampling scheme generates a number of samples, providing an array with rows for each experiment, and columns for the input parameters. The total number of experiments depends on the number of samples and whether the second order indices should be calculated. The number of samples (n) needs to be 2^n, therefore the sample size should be e.g. 512, 1024, or 2048.

For a problem consisting of five parameters (excluding the calculation of second order indices), the first analysis (sample size 1024) resulted in an array of 7168 experiments. The analysis results of the first analysis showed large confidence bounds. Increasing the sample size generally improves the confidence bounds, therefore the analysis was run again with a sample size of 2048 and 4096. The analysis with a sample size of 2048 resulted in 14336 experiments. Since the confidence bounds remained large, the analysis was repeated with a sample size of 4096 (28672 experiments). The confidence bounds of the latter were acceptable, mostly within the 0.05 bounds. Because of the high computational costs (the analysis with a sample size of 4096 took over 90 hours to run), no analysis with larger sample sizes were attempted.

Variance of the system analysis

The model outcomes of ABM's vary with parameter changes, and this can influence the variance of the model output. As the variance of the model outcome can differ across parameter settings, it is relevant to assess the variance of the model settings of non-baseline experiments (Lee et al., 2015, p. 5). For the OFAT analysis the variable changes are within the bounds of the parameter. For the system analysis, some variables are varied using values outside these bounds. Because of time constraints, an additional analysis of the parameter bounds of the system analysis was not added.

Variance due to randomization

When performing a quality check on the results of the OFAT experiments, a large variance was observed between the original and the control run experiments. Despite increasing the number of runs this variance remained. At 200 runs, the variance within experiment was stable with p = 0.01. However, variance was observed when comparing two different experiments.

The explanation for this strange occurrence of variance *between* experiments can be found in the random number generator used in NetLogo. As most complex ABMs, the LUSES model uses a random number generator in certain parts of the code: for example to randomly pick a parameter value within a certain range. To do so, NetLogo uses pseudo-random numbers by creating random seeds using a deterministic generator. This means a random seed (a single value) is being generated using the time and date of that moment. The algorithm used by NetLogo uses this so-called random-seed value to generate a sequence of numbers. For example, the random seed value of 24 will always produce the same sequence of numbers, though this sequence is different when using another random seed value. The use of this random seed value allows for a certain measure of randomness within agent-based models.

This creation of random seeds by the deterministic generator, based on the date and time, means that experiments started on different times use different random-seed values, and therefore have different random values throughout the experiment. Experiments that are conducted in one run use the same random-seed value, and therefore use the same random values throughout the experiment (Wilensky, 1999).

Tests with alternative code for the random number generator showed the LUSES model responds extremely sensitive to the randomly generated factors in the model. A combination of the sensitivity of the LUSES model to the randomly generated parameter values, and the model using the same random seed value for experiments done in one setting, causes large variation between experiments (despite taking the average value of many iterations).

A solution for this variance due to the random number generator is to force the model to generate a new random-seed every time the model initialized the setup and the go command. This means every single run is using a different random seed (based on the time and date), instead of every new experiment (of 200 runs). This decreases the variance between experiments. The variance analysis therefore was run using this change.

Conclusion

This section aimed to answer the question: "how to adapt the LUSES model to perform a quantitative evaluation?". This adaptation was done in three iterative parts: first, scripts for automated data gathering were written, using a link between Python and NetLogo. Secondly and simultaneously, to allow for data extraction from the NetLogo model, reporters were written and some additional sliders were added to the NetLogo interface. The third process was the variance analysis, which was aimed at determining the number of runs needed to achieve variance stability for all reporters, both within and between experiments.

5.3 RQ3: Robustness of model parameters

An answer to research question 3, "how to assess the robustness of the model output due to parameter settings and their interactions?", is provided by performing an OFAT analysis and a Sobol' analysis. These analyses are discussed in this section. The results of the OFAT analysis are discussed in a sub-section for each of the main six variables. For each variable, the outcomes of the different reporters are discussed in three groups: the behavioural reporters, the need satisfaction reporters and the land use reporters. Each sub-section ends by a short summary of the main findings for that variable. For each reporter, the figures illustrate for each time step the amount that scenarios differ from the baseline scenario.

The results of the Sobol' analysis are discussed using the three reporter groups: behavioural, need satisfaction and land use, and discussing the five variables for each reporter group. The results of this analysis are depicted using one figure for each reporter, these figures show the amount of output variance that is explained by each of the main variables.

5.3.1 OFAT analysis

For almost all variables and reporters, fluctuations of the prices of crops can be observed to have a large influence on the output variance. Strong reactions can be seen around year 25-28 for almost all variables and reporters. Figure 5.3.1 shows the prices that are used for the four different crops. The large fluctuations occur especially when the prices of land use 3 drop around year 26. These fluctuations continue as the prices of land use 4 increase around year 28. The drastic changes of the prices of land use 4 between year 0-5, and of land use 2 between year 10-15 do not have the same impact. These collaboratively owned land uses have prices that peak for a short amount of time, and are very low before that. The influence of the cognitive effort might be the reason that the model

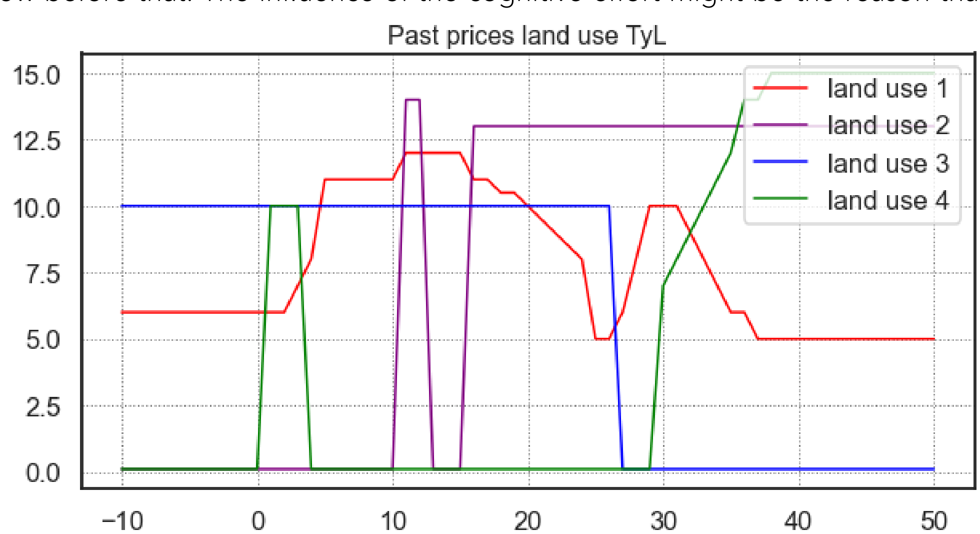

Figure 5.3.1 *The prices of the four land use types throughout the model*

responds less extreme to these changes, compared to the changes of land use 3 around year 26. These fluctuations also occur in the results of the systems assumptions analysis.

I. Aspiration

In the LUSES model, the value of the Aspiration variable is used to assess whether the agent is satisfied, by comparing the aspiration level with the level of overall need satisfaction. For the baseline scenario, each agent is appointed an Aspiration value between 0.001 and 1. To analyse the robustness of this variable, 11 parameter values (between 0.001 and 1) were compared with the baseline scenario (see the values in the legend of figure 5.3.1a).

Behavioural reporters

The Aspiration variable shows extreme values for the behavioural strategies. The four behavioural reporters show values deviating from the base scenario, ranging from -75 to 75 percent. The scenario values are quite even until year 26, fluctuating more after the 26 year mark (see figure 5.3.1a). Lower aspiration values lead to an increase in the *repeat* strategy and the *imitate* strategy, especially after year 26. These are behavioural strategies that are automated, and that are selected because of a high satisfaction. Higher aspiration values lead to more *optimising* and *inquiring* behaviour (low satisfaction, reasoned strategies), especially before the year 26. The scenario where the Aspiration factor is 0.0001 stands out from the rest, showing a larger (relative) difference from the baseline scenario than the other scenarios. The lower parameter values (0.0001 and 0.1) and the higher parameter values (0.7, 0.8, 0.9, 0.999) especially deviate from the values of the baseline scenario.

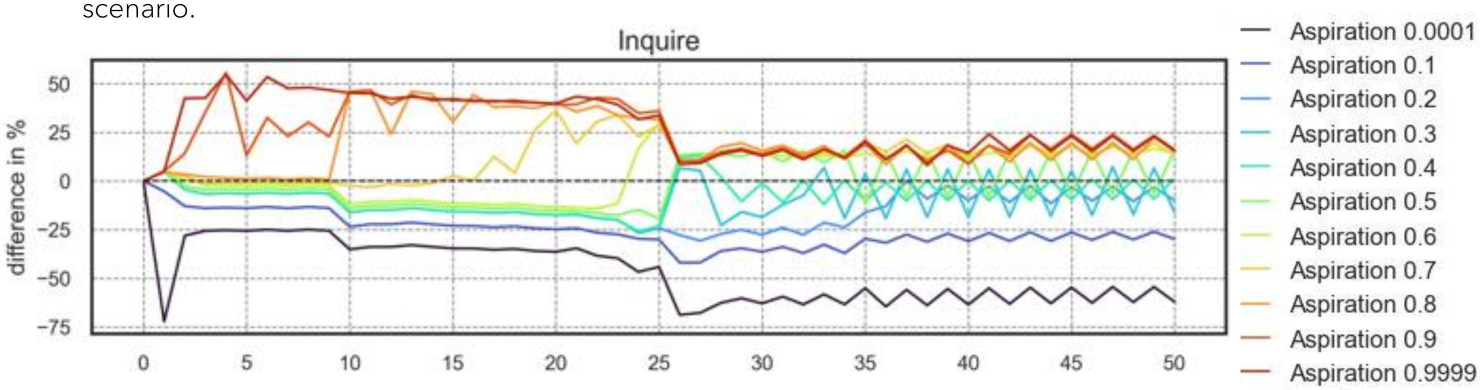

Figure 5.3.1a The effect of different parameter values of Aspiration on the behavioural strategy "inquire".

Need satisfaction

The Aspiration variable has little influence on the *social need* reporter (values between -0.5 and 0.5 percent). For the *personal*, *existence* and *overall need satisfaction*, the values 0.0001, 0.1, 0.8, 0.9

and 0.9999 are quite unstable, and deviate a lot from the baseline scenario (especially after year 25). The influence on the *personal need* reporter is moderate, with values between -5 and 2.5 percent. For the *existence* and *overall need satisfaction* reporters, alternative scenarios show a large deviation from the baseline scenario. Aspiration value 0.0001 (and 0.1) show extreme, but quite stable increases before the 24 year mark. The parameter values 0.8, 0.9 and 0.9999 have a negative impact on these reporters before year 26, and are quite unstable. After year 30, all scenarios show extreme fluctuations around the baseline value. Less extreme parameter values are close to the baseline scenario throughout.

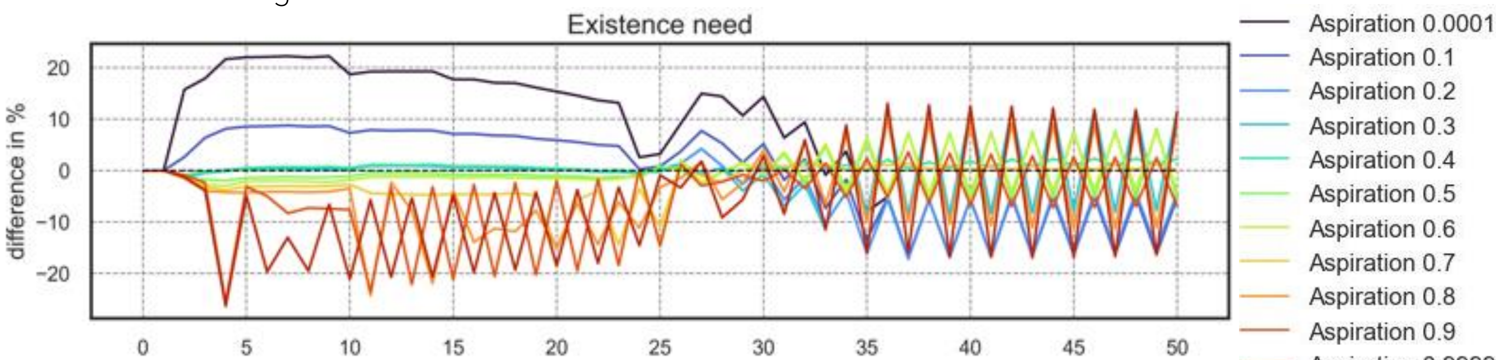

Figure 5.3.1b The effect of different parameter values of Aspiration on the existence need satisfaction.

Land use distribution

For the land use reporters, most alternative scenarios have values between -20 and 20 percent compared with the baseline scenario. The single land use reporters (LU 1, 2, 3 and 4) show extreme, fluctuating values before year 26 for the values 0.8, 0.9 and 0.9999. After year 26, all scenarios spread out more, showing ordered (but fluctuating) results for the reporters of *land use 2* (collaborative, cleared field land use) and *land use 3* (individual, forest-based land use), as can be observed in figure 5.3.1c. For *land use 1* and *land use 4*, the scenarios fluctuate a lot after year 26 but are not clearly

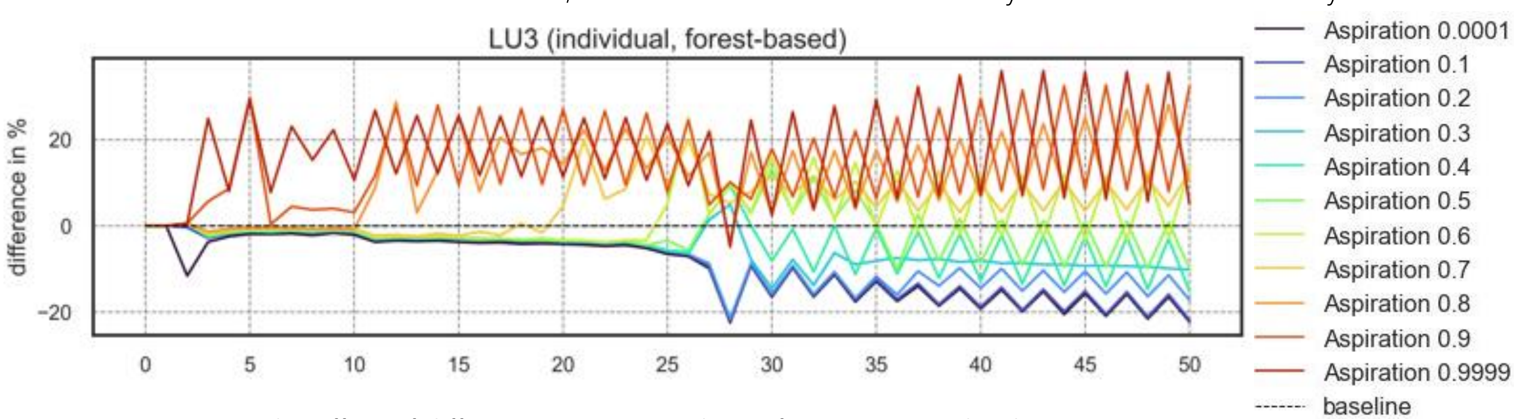

Figure 5.3.1c The effect of different parameter values of Aspiration on land use 3.

ordered. High Aspiration values lead to an increase of the individual land use types (*land use 1* and *land use 2*).

To sum up, variations of the variable Aspiration have a large but stable impact on the behavioural reporters. The existence and overall need satisfaction reporters are strongly influenced as well, showing much fluctuation after year 30. The land use reporters are strongly influenced, and show big fluctuations for extreme values throughout, and for moderate values after year 26. The model reacted especially strong on extreme values (0.0001, 0.1, 0.8, 0.9 and 0.999). The differences of the behavioural strategies are especially large.

II. Cognitive effort

In the LUSES model, the Cognitive Effort variable determines the amount of time an agent remembers land use prices. For the variable of cognitive effort, 10 alternative parameter values were compared with the baseline scenario, which randomly selected a value between 1 and 10 for each agent.

Behavioural reporters

Changes of the Cognitive variable have a moderate effect on the behavioural reporters. The model reacts especially sensitive to different parameter values between the 24 and 34 year mark. Up to year 24, the influence of the scenarios is ordered, however, during and after this 10 year period the scenarios are less ordered. A low cognitive effort has a positive effect on the percentage of agents engaging in repeating and imitating behaviour (behaviour chosen when agents have a high need satisfaction). It has a negative impact on the optimizing and inquiring strategies (chosen when the need satisfaction is low). The alternative scenario with 1 year cognitive effort is striking, showing a strong negative influence for repeating and imitating strategies, and a strong positive influence on optimizing and inquiring strategies (contrary to the other scenarios with low cognitive effort).

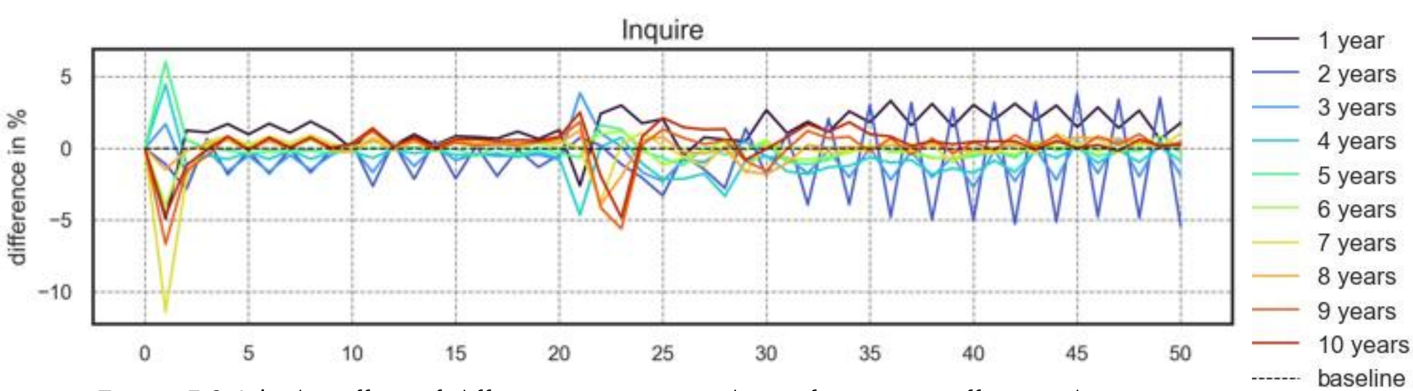

Figure 5.3.1d. The effect of different parameter values of cognitive effort on the inquiring behavioural strategy.

Need satisfaction

The Cognitive variable shows moderate differences for the personal need satisfaction reporter (-10 to 8 percent) and the existence and overall need reporter (-7 to 10 percent), but only small differences for the social need reporter (-0.4 to 0.1 percent). The existence and overall need reporter show a positive influence of low cognitive effort on agents' need satisfaction, and a negative influence of high cognitive effort. For the personal need reporter this is mostly the other way around. Noteworthy is how for both the personal, existence and overall need satisfaction, the alternative scenario with 1 year shows more extreme results than the experiment with 10 year cognitive effort (see figure 5.3.1e).

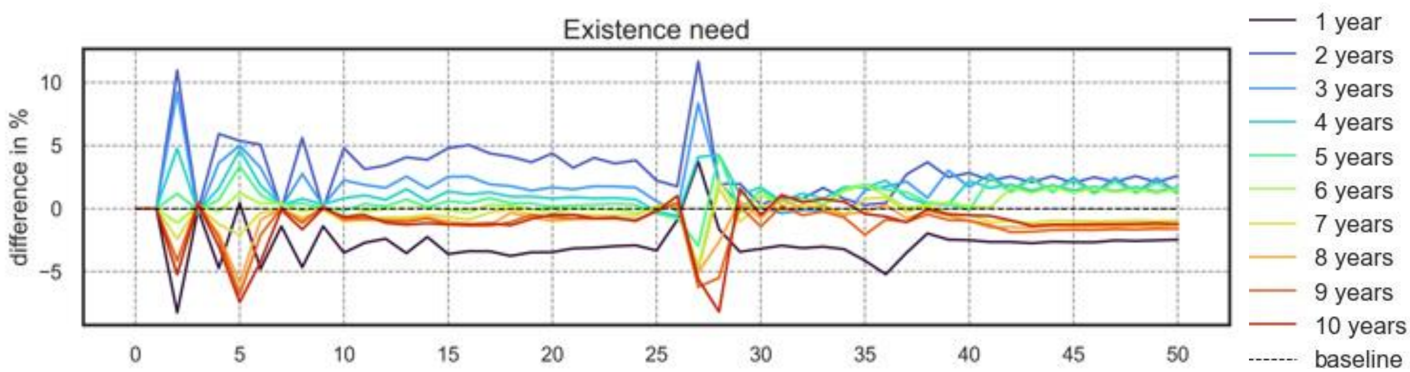

Figure 5.3.1e. The effect of different parameter values of cognitive effort on the existence need satisfaction.

Land use distribution

The land use reporters all show an extreme spike around year 27 or 28. The fluctuations and big differences compared to the baseline scenario start around year 24, and after the initial spike the fluctuations even out around year 36/37. Low cognitive effort causes a positive spike for *cleared field* and *individual land uses*, and a negative spike for *forest cover* and *collaborative land uses* (mostly between year 225 and 27). High cognitive effort causes the opposite, see figure 5.3.1f.

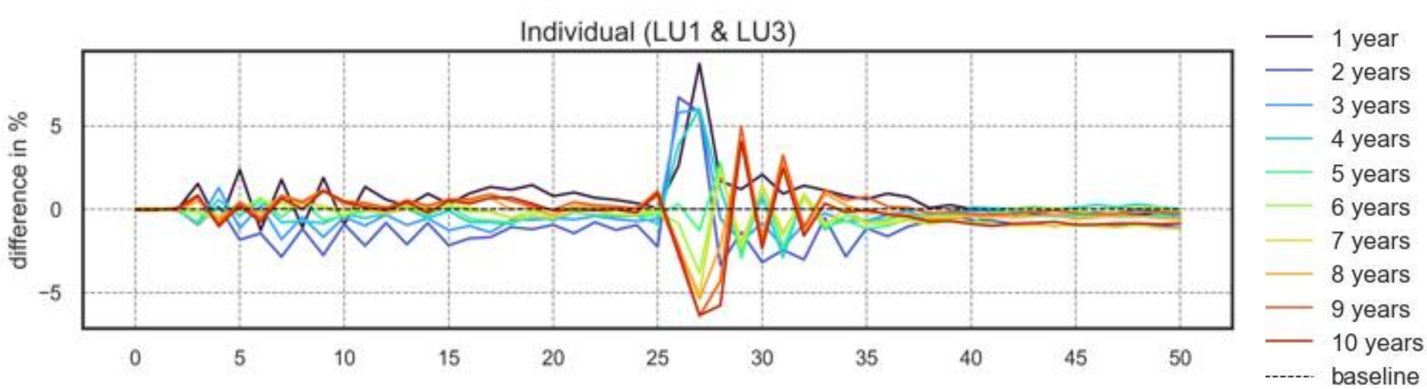

Figure 5.3.1f. The effect of different parameter values of cognitive effort on individual land use.

To sum up, variations of the Cognitive variable have a moderate impact on all reporters (except *social need satisfaction*). The values of the behavioural reporters are fluctuating (especially between year 24 and 34). The Cognitive variable has a negative influence on the *existence* and *overall need* satisfaction, and a positive effect on the *personal need satisfaction* values. For the land use reporters, the reporters values deviate strongly between year 24 and 36. The parameter value 1 is noteworthy, since it behaves contrary to the other parameter values for the behavioural and need satisfaction reporters; it shows more extreme values than the 10 years experiment.

III. Uncertainty

The Uncertainty variable indicates the uncertainty tolerance level. This is used to determine whether an agent is (un)certain, by comparing the tolerance level with the experienced uncertainty. For the Uncertainty variable, 11 alternative parameter values were compared with the baseline scenario, which randomly selected a value between 0.0001 and 0.9999 for each agent.

Behavioural reporters

The behavioural reporters show large differences with the baseline scenario for all behavioural strategies (values range between -40 to 40 percent). The different experiments are distinctly ordered, and show gradual changes (only few large fluctuations). The differences with the baseline scenario decrease after the 27 year mark for the *inquire* and *optimizing* reporter, and increase for the repeat and imitate reporter. Lower Uncertainty values cause an increase of optimizing and imitation strategies, and a decrease in repeating and inquiring strategies. Higher uncertainty values have relatively less impact than lower uncertainty values.

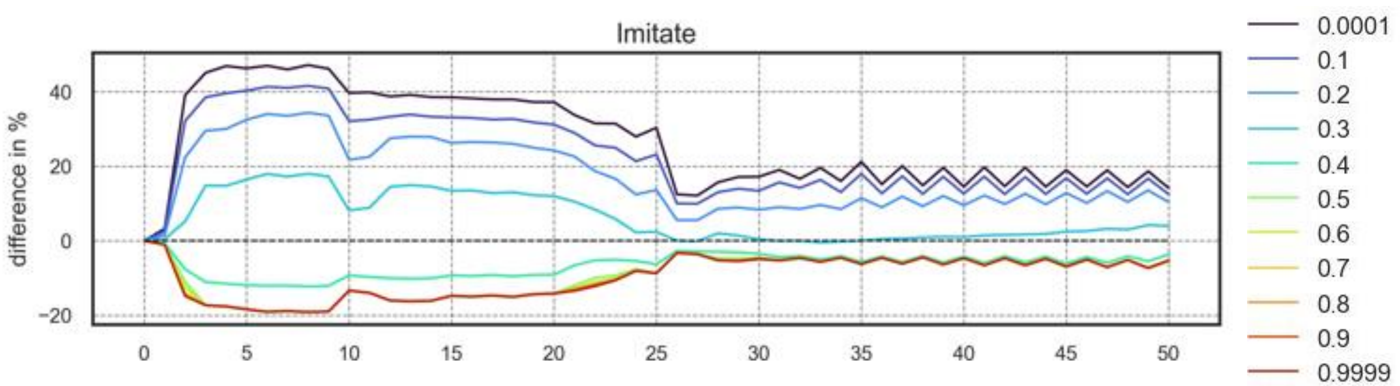

Figure 5.3.1g. The effect of different parameter values of uncertainty on the behavioural strategy imitate

Need satisfaction

Variations in the Uncertainty value show small changes for the social need reporter (between -0.1 and 0.3 percent), the personal need reporter (between -0.5 and 0.5 percent), and for the existence need and the overall need reporter (-2 to 1.5 percent).

Land use distribution

The different uncertainty values have little impact on the land use choices. The Uncertainty scenarios range from -1 to 1 percent.

To sum up the effects of the Uncertainty variable, both land use and need satisfaction values are barely impacted by changes in the Uncertainty values. The behavioural strategies, however, are impacted greatly. Higher uncertainty values have relatively less impact than lower uncertainty values on the behavioural strategies.

IV. Existence need

The (Existence, Social and Personal) need satisfaction variables indicate the percentage of the overall need satisfaction that is determined by either the existence, social or personal need satisfaction. For the variable of the Existence need, 5 parameter values were compared with the baseline scenario. The baseline scenario randomly selects a value between 0.80 and 0.99 for each agent. The Existence need value was set to a certain value for *all* agents in the alternative scenarios. For all reporters, the experiments with existence need values of 0.8, 0.85 and 0.95 show a lot of fluctuation, while the experiment with a value of 0.9 does not. The value of 0.9 is close to the average value of the baseline scenario, which lies at 0.895. In addition to this, for all reporters (except *social need satisfaction*) a trend can be observed where values peek at year 1, showing low and high Existence need values ordered above and below the baseline. After year 1 the scenarios switch order until year 24, after which the scenarios switch back to the original order. For all reporters (except *social need satisfaction*), after year 24 there are more fluctuations and the difference with the baseline scenario becomes more pronounced.

Behavioural reporters

The behavioural reporters *optimise* and *imitate* differ only slightly from the baseline scenario, with values mostly between -1 and 1 percent. The reporters *repeat* and *inquire* show more pronounced deviations, mostly between -4 and 3 percent. High Existence need values cause the reporters *optimize* and *inquire* to peek at the first time step, dip until year 24 and then rise again until the end of the experiment, and vice versa for the reporters *repeating* and *imitating*.

Need satisfaction

In terms of need satisfaction reporters, the social need reporter shows values between -0.1 and 0.2 percent, indicating a neglectable impact. Variations of the existence need variable have a small effect on the personal need satisfaction (between -0.5 and 1 percent after year 24). The existence need satisfaction shows ordered, small deviations before year 24. A higher existence need value has a negative impact on the existence need satisfaction, while a lower existence need value has a positive impact. After year 24, the differences between scenarios become bigger and fluctuate more around the baseline. For the overall need reporter, difference spike at the beginning of the experiment, after which there is little difference with the baseline scenario. After year 24 differences grow, and show a positive impact of lower existence need values, and a negative influence of higher existence need values.

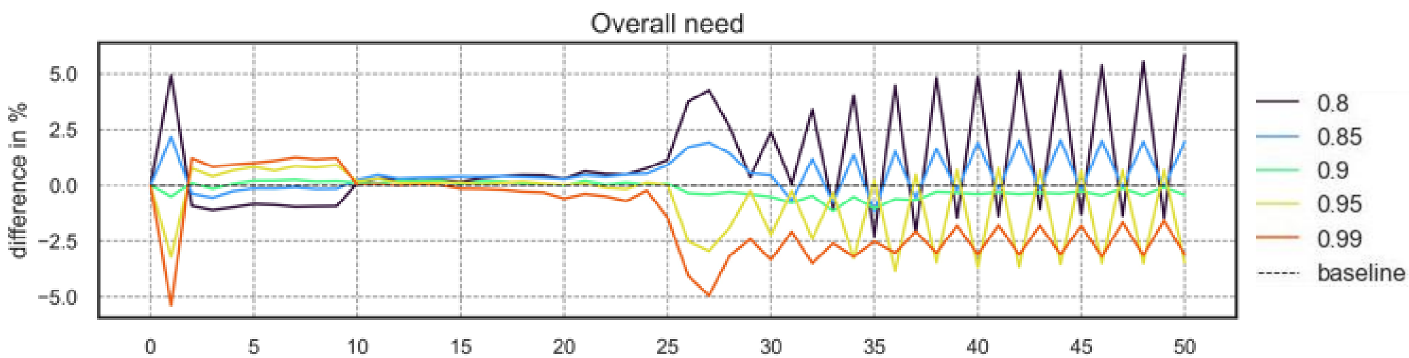

Figure 5.3.1g. The effect of different parameter values of existence need on the overall need satisfaction.

Land use distribution

Land use reporters are stable and close to the baseline scenario before the 27 year mark, after which the results diverge further from the baseline, in a ordered manner for land use 2 and 3. The reporters of land use 3 and land use 4 are effected more strongly (values between -5 and 5 percent) while land use 1 and 2 are effected less (values between -2 and 2 percent). The combined reporters all show values that deviate between -4 and 4 percent from the baseline scenario. For cleared field and collaborative land use, lower existence need values cause an increase of the percentage of land use (and higher values cause a decrease). For the individual and forest cover land the scenarios behave in the opposite way.

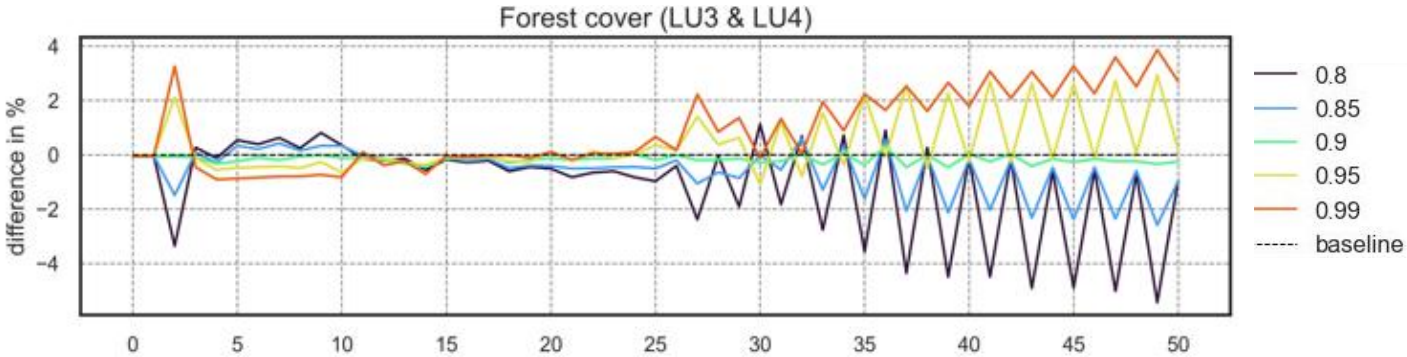

Figure 5.3.1h *The effect of different parameter values of existence need on forest cover land use.*

To sum up the results of the Existence need variable, for all reporters the experiments with values of 0.8, 0.85 and 0.95 show a lot of fluctuation. After year 24, fluctuations in the model increase for all reporters. In addition to this, for all reporters (except the social need reporter) a trend can be observed where values peek at year 1, showing low and high Existence need values ordered above and below the baseline. After year 1 the scenarios switch order until year 24, after which the scenarios switch back to the original order. The reporters *repeat* and *inquire* are moderately impacted, as well as the *existence* and *overall need satisfaction* and the land use reporters.

V. Social need

For the variable of the Social need importance, 5 parameter values were compared with the baseline scenario. The baseline scenario randomly selects a value between 0.05 and 0.10 for each agent (equal to the personal need importance). The social need value was set to a certain value for *all* agents in the alternative scenarios, independent from the personal need importance.

For all reporters, the experiments with social need values of 0.005, 0.025 and 0.1 show a lot of fluctuation. For all reporters (except *social need satisfaction*), after year 24 there are more fluctuations overall, and the difference with the baseline scenario becomes more pronounced.

Behavioural reporters

All behavioural reporters show quite stable, ordered results before year 26, and ordered but fluctuating, unstable results after year 29. With values diverting -1 to 1.5 percent compared with the baseline scenario, the *optimizing* and *imitating* behavioural strategies do not react strongly to changes in the Social Need variable. *Repeating* and *inquiring* behaviour shows moderate reactions (between -4 and 4 percent). For *repeating* and *imitating* behavioural strategies, higher social need values result in more agents engaging in the behavioural strategy, and lower social need values results in less agents engaging. For the *optimizing* and *inquiring* strategies this is the other way around.

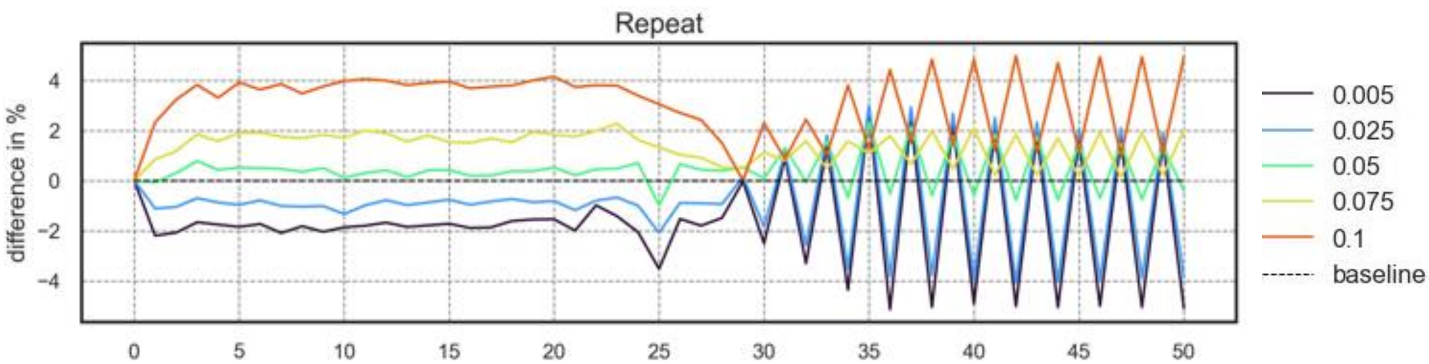

Figure 5.3.1i The effect of different parameter values of social need on the behavioural strategy repeat.

Need satisfaction

In terms of need satisfaction reporters, the social need reporter shows values between -0.2 and 0.0 percent, indicating a neglectable impact. The personal need reporter shows small but stable and ordered differences with the baseline scenario (-2 to 1 percent), which strongly fluctuate after year 28. The same can be observed for the existence and overall need satisfaction: before year 28/29 the scenarios are stable and ordered, and afterwards they are still ordered but fluctuate greatly. The scenarios with social need values 0.005, 0.025 and 0.1 fluctuate the most. A high social need value (0.1) causes a higher overall need satisfaction. A low social need satisfaction variable (0.005) causes a lower overall need satisfaction.

Land use distribution

The social need scenarios have a moderate influence on the land use choices (average values between -5 and 5 percent). Low social need values impact the individual and forest cover land use positively, and impacts the cleared field and collaborative land use negatively. High social need values have the opposite effect. The differences are small and stable until year 25/26, but differences grow and fluctuate in the years following.

To sum up the results of the Social Need variable, after year 24 there are strong fluctuations and larger differences with the baseline scenario for all reporters (except *social need satisfaction*). Especially the experiments with social need values of 0.005, 0.025 and 0.1 show a lot of fluctuation. The Social Need variable has a moderate impact on *repeating* and *inquiring* behaviour, existence and overall need satisfaction and on the land use reporters.

VI. Personal need

For scenarios of Personal need, 5 parameter values were compared with the baseline scenario. The baseline scenario randomly selects a value between 0.05 and 0.10 for each agent (equal to the Social need variable). The Personal need value was set to a certain value for *all* agents in the alternative scenarios, independent from the Social need importance.

For all reporters, the experiments with Personal need values of 0.005, 0.025 and 0.75 show a lot of fluctuation. After year 24 there are more fluctuations for all reporters (except *social need satisfaction*), and the difference with the baseline scenario becomes more pronounced.

Behavioural reporters

The alternative experiments for the Personal need variable have a small impact on the choice of behavioural strategies (averages between -2 and 2 percent). The scenarios are ordered and quite stable before year 25, fluctuating more afterwards. Higher Personal need importance positively influences the percentage of agents engaging in *repeating* and *imitating* behaviour, and vice versa for the *optimizing* and *inquiring* strategies.

Need satisfaction

Changes of the social need satisfaction are neglectable (averages between -0.3 and 0.1). For the personal need satisfaction the scenarios show even, ordered differences compared to the baseline scenario. Lower personal need importance causes a lower personal and overall need satisfaction, and vice versa for the higher values. After year 25-27 more fluctuations occur for the personal, existence and overall need satisfaction. Noteworthy is the absence of extreme fluctuations around the price changes, which often occur between year 25-28. This is only visible for the existence need reporter, and only moderately.

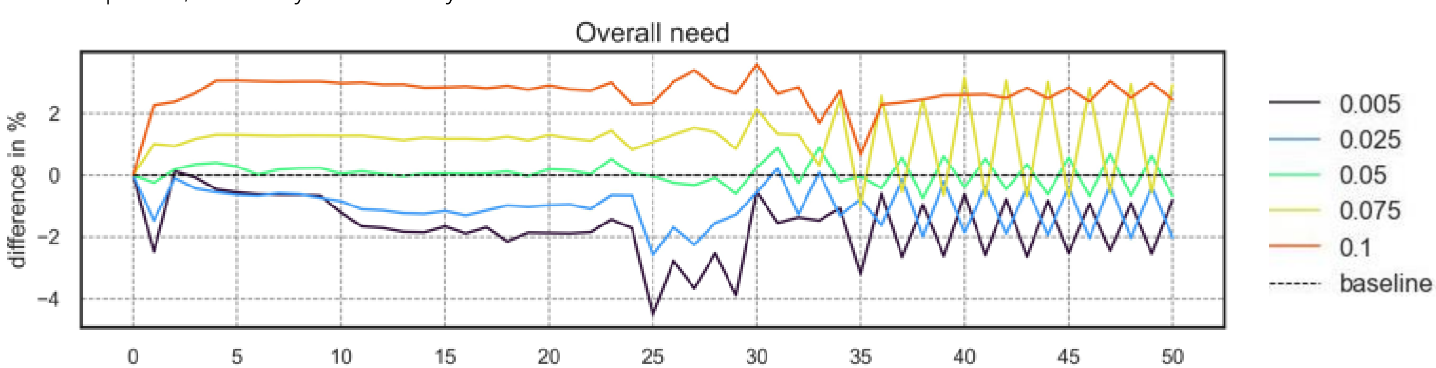

Figure 5.3.1j The effect of different parameter values of personal need on the overall need satisfaction.

Land use distribution

The Personal need scenarios have a small influence on the land use choices, with most values between -2 and 2 percent. *Land use 3* and *4* are influenced strongest. Low Personal Need values impact the *individual* and *forest cover* land use positively, and impacts the *cleared field* and *collaborative* land use negatively. High Personal Need values have the opposite effect.

To sum up the results of the Personal Need variable, for all reporters after year 24 the alternative scenarios show strong fluctuations (except *social need satisfaction*). The *personal* and *overall need satisfaction* are moderately influenced, while there is a small influence on the other reporters (except the *social need satisfaction*, which is barely influenced).

5.3.2 Sobol' analysis

The Sobol' analysis does not show the variance throughout the experiment, for each time step, like the OFAT analysis did. Instead the values indicate the model output variance for all time steps. The Sobol' analysis draws parameter values from within the bounds of the baseline scenario, therefore testing the same range of values as the OFAT analysis. The strength of the Sobol' analysis for this research is the indication of interaction effects. The Sobol' analysis provides two indices: the first order indices and the total order indices (Saltelli et al., 2010). First order indices (S1) indicate the direct contribution of a parameter to the model variance (without interaction effects). Total effect indices (ST) measure the total contribution of a parameter, therefore including interaction effects. The first order indices are always equal to or smaller than the total order indices (Herman & Usher, 2017). The S1 results can be compared with the outcomes of the OFAT analysis.

These results were gathered by running 28672 different experiments. In the graphs, the confidence bounds are visualized as a black line at the top of the bars. The confidence bounds of the results are mostly beneath the value of 0.05. The results are discussed for the three groups of reporters.

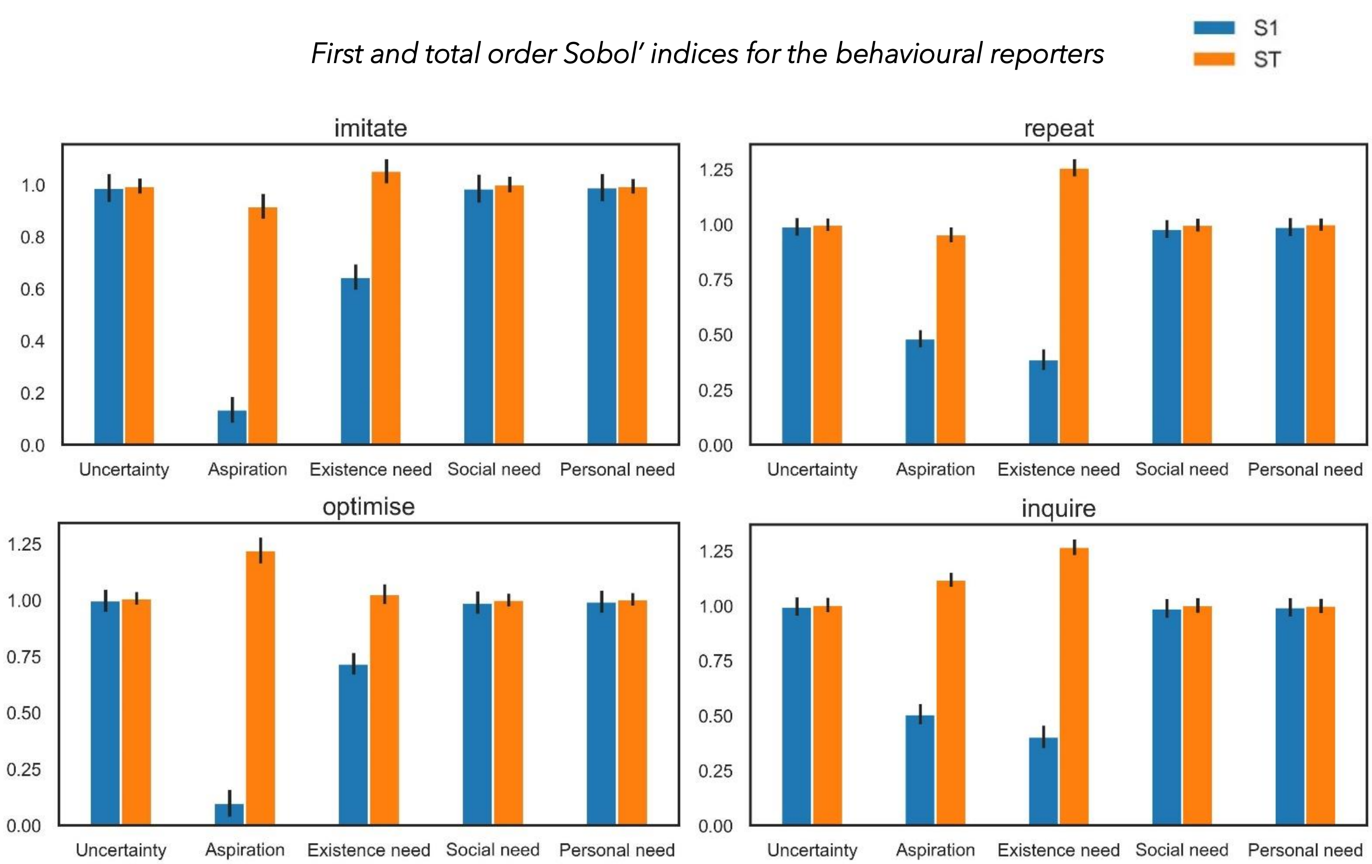

Figure 5.3.2a *The results of the Sobol' analysis for the behavioural reporters*

I. Behavioural strategies

The behavioural strategies (see figure 5.3.2a) have the most exceptions regarding the confidence bounds. For the total order (ST) indices, all confidence bounds are below the p-value 0.05, except for the Aspiration variable of the *optimise* reporter. For the first order (S1) indices of the *optimise* reporter, the confidence bounds are bigger than the p-value for all except the Social need variable. For the *imitate* reporter, the confidence bounds of the S1 indices of the Uncertainty, Social need and Personal need variables are bigger than 0.05, as well the Existence need variable. For the *repeat* reporter, the latter is also larger than the p-value. For the *inquire* reporter, the S1 confidence bounds of the Aspiration reporter are bigger than 0.05.

When compared with the OFAT analysis results, the results of the Sobol' analysis are striking. For the OFAT analysis, the Aspiration parameter caused large variations of the output, followed by the Uncertainty variable. The Cognitive variable and the Need satisfaction variables all had a small or very small impact on the output variance. For the Sobol' analysis however, the Aspiration and Existence need variables have the smallest impact on the model output – especially for the reporters of *optimizing* and *imitating* behaviour. The Uncertainty, Social need and Personal need variables have a large impact for the first order indices, which seems to contradict the results of the OFAT analysis. For the total order indices, the Aspiration and Uncertainty variables show the biggest differences. The Existence need variable has the highest influence on the output variance for the *imitate*, *repeat* and *inquire* behavioural reporters. For the *optimise* behavioural reporter, the Aspiration variable has the largest influence.

II. Need satisfaction

The results for the need satisfaction reporters (figure 5.3.2b) all are within the 0.05 margin for the confidence bounds, except for the S1 indices of the Aspiration variable of the *personal need* reporter.

Compared with the OFAT analysis results, the Uncertainty and Existence need variables are noteworthy. In the OFAT analysis, the Uncertainty variable has little influence on the output variance of all four need satisfaction reporters. The Sobol' analysis shows a moderate influence on the *existence* and *personal* need reporters, and a high influence of the variance of the *overall* need reporter. The OFAT analysis shows that the Existence need variable has little influence on the *social* and *personal* need satisfaction reporters, and a moderate impact on the *existence* and *overall* need reporters. The S1 indices of the Sobol' analysis show the Existence need variable to have no impact on the *existence* need variable, and a small influence on the *personal* need variable.

The results of the Sobol' analysis for the *social* need reporter are interesting: in line with the OFAT results, the S1 indices show the variables to have almost no impact on the variance of the *social* need reporter. When taking into account the interaction effects, the full extent of the variance of the *social* need reporter is explained. This can also be observed for the other need satisfaction reporters: not all variance is explained by the S1 indices, however the full variance is explained by the ST indices.

Figure 5.3.2bThe results of the Sobol' analysis for the need satisfaction reporters

III. Land use reporters

For the land use reporters (see figure 5.3.2c), all confidence bounds are within the 0.05 margin, except for the S1 indices for the Existence need variable of the *land use 2, land use 4, forest cover* and *cleared field* reporters.

The OFAT analysis showed a large influence of the Aspiration variable on the land use reporters, a small influence of the need sat variables and a very small influence of the Uncertainty variable. Similar to the *existence* and *social* need satisfaction reporters, the S1 indices show the Existence need variable has almost no influence on the land use reporters. All other variables have a large influence on the land use reporters according to the S1 indices. For the ST indices, the Existence need variable is indicated to have an extremely large influence on the land use reporters. The influence of the other variables increases slightly with the added interaction effects, but the Existence need variable shows a lot more influence on the output variance due to interaction effects.

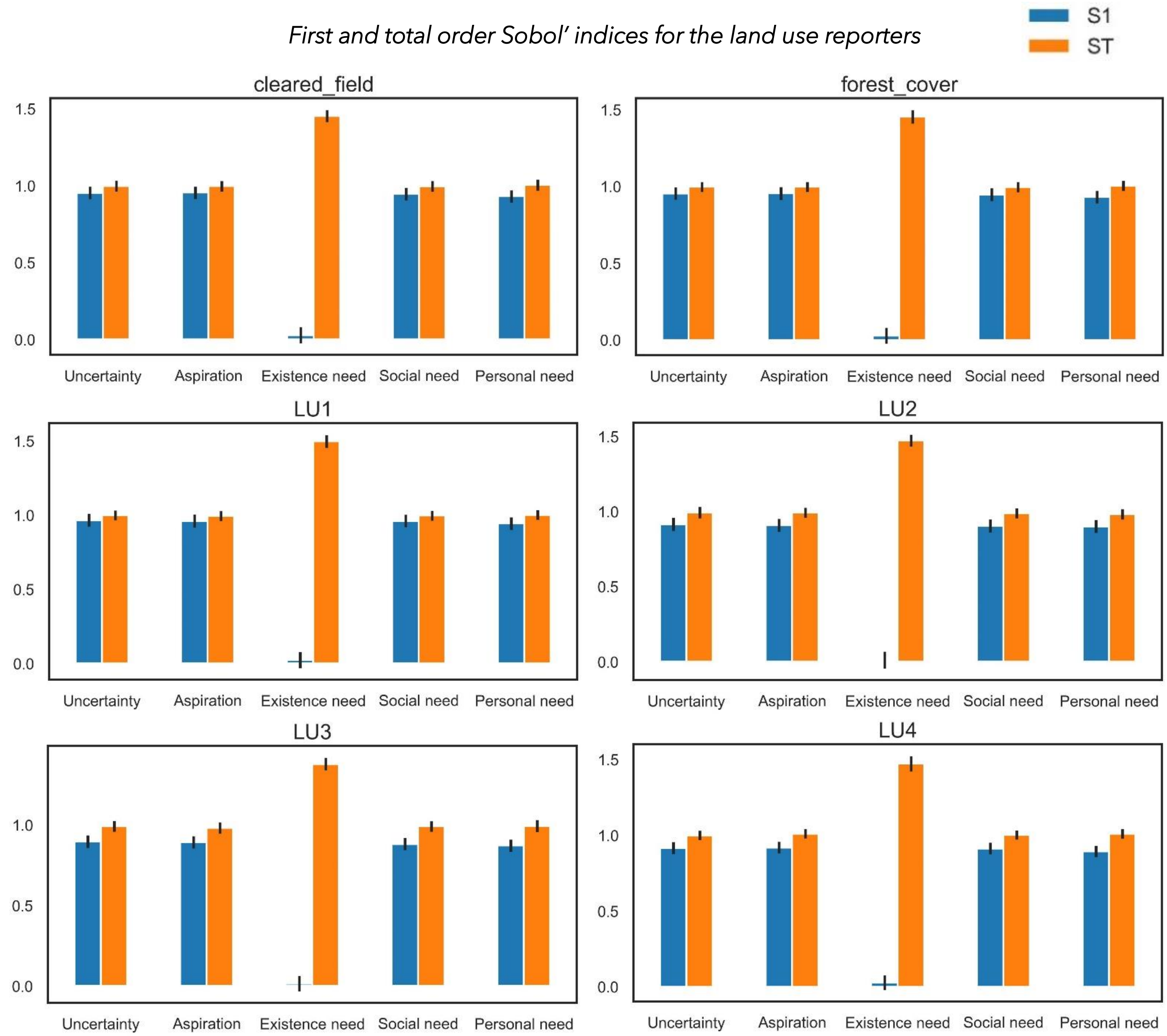

Figure 5.3.2c *The results of the Sobol' analysis for the land use reporters*

5.4 RQ4: System assumptions

To answer the research question "what impact can be expected by change of 'system' assumptions?", a systems analysis was performed. This was done for three topics:

1. Cognitive function,
2. Peer networks,
3. Need satisfaction ratios.

For the cognitive function, two experiment topics were explored: the influence of memory decay and the influence of the length of memory. For the peer network, two experiment topics were explored as well: the influence of peer network sizes and the influence of geographical weights of the peer selection. For the need satisfaction ratios, the scenarios consisted of different experiments with the variables of Existence, Social and Personal need satisfaction. Just like the OFAT analysis, the scenarios were run for 50 time steps, using the averages of 200 runs. Another similarity are the influence of fluctuations of the prices of crops, which can be observed to have large influences on the model. Strong reactions can be seen around year 25-28 for almost all variables and reporters.

5.4.1 Experiments with the cognitive function

Length of memory

For the memory length experiment, four scenarios were compared with the baseline scenario, alternating the duration of agents' memory. Agents' memory was set to 15, 20, 25 and 30 years, and compared with the baseline value where agents' memory is randomly set between 1 and 10 years.

Behavioural reporters

Overall, a longer memory showed to have a positive effect on the percentage of agents engaging in the behavioural strategies *optimising* and *imitating*, and a negative effect on the percentage of agents choosing *repeating* and *inquiring* strategies. The scenarios with 15 and 20 years of memory do not show very large differences with the baseline scenario, however, the scenarios with 25 and 30 years of memory show more pronounced differences. For *inquiring* and *imitating* behavioural strategies, the differences became larger after year 21, and slowly declined after year 30. The influence of a longer memory can be observed in the way scenarios with a longer memory take longer to return to the baseline value (see figure 5.4.1a).

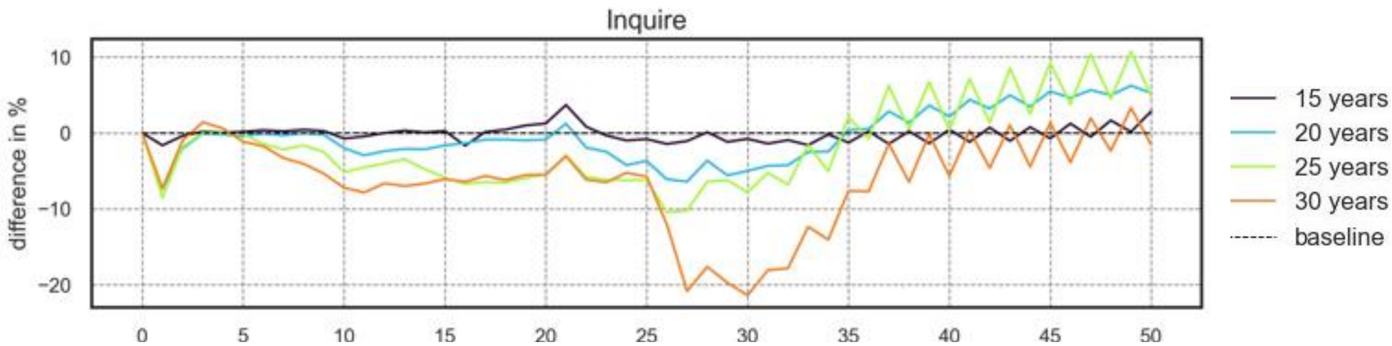

Figure 5.4.1a. The effect of cognitive effort (duration of memory) on the behavioural strategy.

Need satisfaction

The social need satisfaction shows very small differences (-0.1 – 0.5 percent). The personal need satisfaction shows larger differences, but only after year 26: a difference of max 2 percent for the 20 year scenario, and 10 and 12 percent max for the 25 and 30 year memory (respectively). The existence need satisfaction also shows larger differences after year 26, there is a short increase of existence need satisfaction (especially for the 30 year memory scenario) between year 26 and 35, after which the existence need declines compared to the baseline scenario (up to -14 percent). The overall need satisfaction is extremely similar to the existence need satisfaction.

Land use distribution

For the land use distribution, the length of memory has a large influence after year 26. Just like for the behavioural strategies, the 15 and 20 year scenarios do not make a big difference compared to the baseline scenario. The 25 and 30 year scenarios, however, have a big influence. For land use 2 and 4 the difference with the baseline scenario fluctuates after year 26, between -2 and 2 for land use 2 and with more impact for land use 4: between -20 and 10 percent. After year 26, the 25 and 30 year memory scenarios cause a steady increase of land use 1 (up to 30 and 50 percent respectively), while causing a steady decrease for land use 3 (-25 and -35 percent respectively). After year 26, increased duration of memory causes a great incline of the cleared field land use, and a great decline of the forest cover land use. Likewise it causes a more gradual increase of individual land use and a more gradual decrease of collaborative land use.

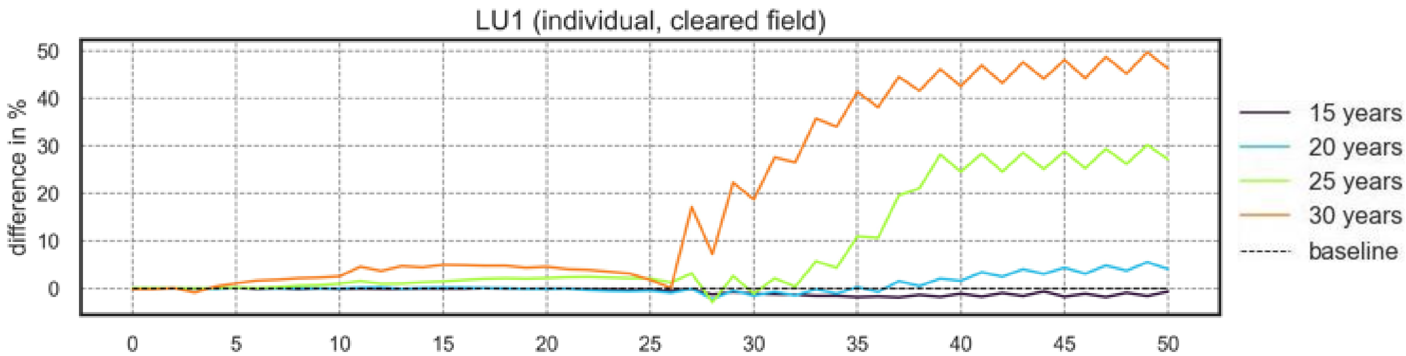

Figure 5.4.1b. The effect of cognitive effort (duration of memory) on the percentage of land use 1.

Cognitive decay

For the cognitive decay comparison, one scenario was compared with the baseline scenario, taking out the cognitive decay of agents' memory. This means agents do not forget attributes in the alternative scenario.

Behavioural reporters

The four behavioural reporters show a common trend: the difference with the baseline scenario increases towards the 26 year mark, shows extreme values between time step 26-29 and afterwards evens out. The behavioural strategies of *repeat* and *imitate* are positively influenced by the absence of cognitive decay. They show max values of 15 and 4 percent respectively between the 26 and 29 time step, and even out to around 5 and 2 percent. The behavioural strategies of *optimise* and *inquire* are negatively influenced by the removal of cognitive decay, the *optimizing* strategy shows a max value of -5 around time step 28, and evens out to around -1.5 percent. The *inquiring* strategy shows a max value of -12.5 percent at time step 29, and gradually returns to a value of -5.5. The strategies of *repeat* and *inquire* are influenced most strongly.

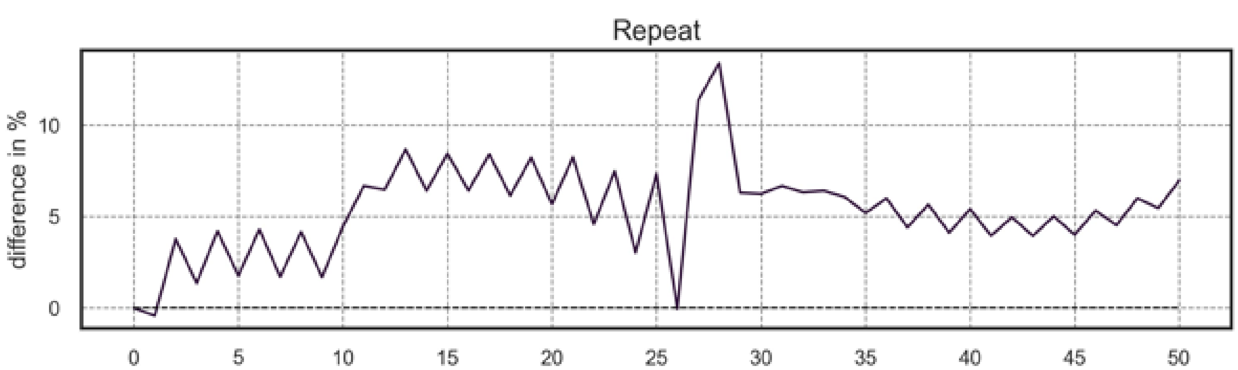

Figure 5.4.1c. The effect of the removal of cognitive decay on the behavioural strategy "repeat"

Need satisfaction

For the need satisfaction reporters, the difference between both the social and the personal need satisfaction of the baseline scenario and the scenario without cognitive decay is very small (between 0 - 0.25 and -1 - 0 respectively). The existence need satisfaction, however, shows large differences. Around time step 26-29, the alternative scenario shows between 14-16 percent more existence need satisfaction. After year 29, this evens out to about 6-10 percent.

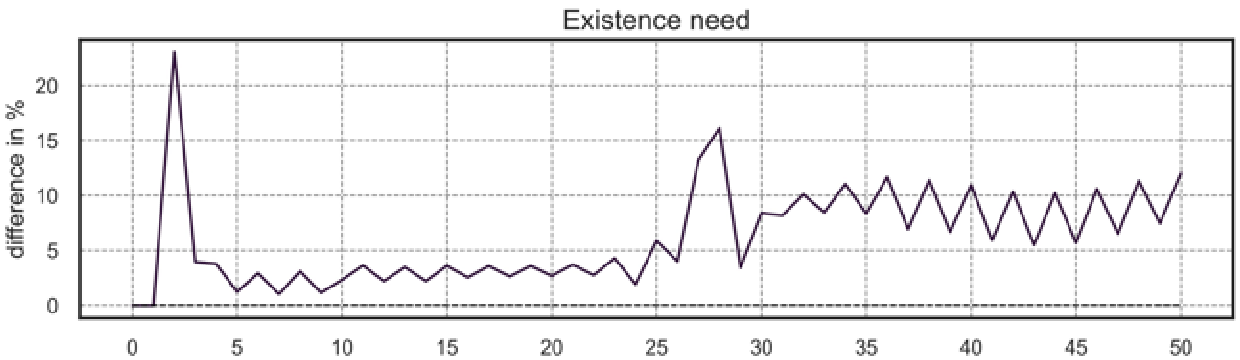

Figure 5.4.1d. The effect of the removal of cognitive decay on the existence need satisfaction

Land use distribution

The land use reporters showed a small and gradual difference with the baseline scenario year 26, however the alternative scenario without cognitive decay showed more extreme values immediately after year 26. After year 30, extreme fluctuations remain. The alternative scenario without cognitive decay results in more land use 2 and 4, and less land use 1 and 3. Noteworthy is that the removal of cognitive decay causes a decline in individual land uses (max value -10 percent), and an increase of collaborative land uses (max value 12 percent). The changes of cleared field land use and forest cover land use are less extreme. Cleared field land use shows an increase (max 2 percent) before the price drop, but after the price drop the cleared field land use percentage fluctuates around the baseline value (-1.5 and 2 percent average). The same happens for the forest cover land use, before the price crash it shows a decline of -2 max, but after the price drop the difference with the baseline scenario fluctuates between -2 and 1.5 percent (average).

Summary of the cognitive function experiments

A longer memory showed to have a positive effect on the percentage of agents engaging in the behavioural strategies optimising and imitating, and a negative effect on the percentage of agents choosing repeating and inquiring strategies. This suggests a longer memory increases the possibility of agents having both a high satisfaction and a high uncertainty, or both a low satisfaction and a low uncertainty. This might be due to the interconnectedness of uncertainty, satisfaction and the expected prices. For example, the calculation of the expected income is based on the prices that are memorized, and influences both agents uncertainty through the expected prices of peers, and influences the existence need satisfaction of optimizing/inquiring agents through the expected income prices. To conclude, a longer memory impacts the likelihood of agents having low satisfaction and low uncertainty, or high satisfaction and high uncertainty.

For the need satisfaction reporters, there is a general increase of existence need satisfaction between year 26 and 35, after which there is a decline. Agents with a long memory show a slower decline of need satisfaction (overall and existence) after sharp price declines.

For the land use reporters, especially the 25 and 30 year scenarios show large differences with the baseline scenario. Compared with the crop prices, agents with a longer memory can be observed to value land use types that have had high crop prices in the past over land use types that have had low crop prices in the past (but that now have high crop prices). Though this behaviour does not reflect reality, this is the expected behaviour for the model.

For the experiments where the cognitive decay is removed, the behavioural reporters show a positive influence on the behavioural strategies *repeat* and *imitate*, and a negative impact on the strategies *optimize* and *inquire*. This indicates the removal of cognitive decay causes agents to have a higher need satisfaction, since *repeating* and *imitating* behaviour is automated and based on a high need satisfaction, while *optimizing* and *inquiring* behaviour is reasoned and based on low need satisfaction. This is confirmed by the large differences of the existence need satisfaction reporter, which even shows a similar pattern throughout the simulation. For the land use reporters, the increase of collaborative land uses and the decline of individual land uses is noteworthy.

5.4.2 Experiments with peer selection

Number of peers

For the number of peers, four scenarios were compared with the baseline scenario, alternating the number of peers selected by each agent. The number of peers was set to 1, 10, 20 and 30, and compared with the baseline value where agents have 5 peers.

Behavioural reporters

For all four behavioural reporters, the scenarios show differences of max -5 to 5 percent compared to the baseline scenario. The difference between the baseline scenario and the alternative scenario of 1 peer is bigger than the difference with alternative scenarios where agents have 10 or 20 peers. The choice of *optimizing* behaviour throughout and *imitating* behaviour before year 26 increases if agents that have only 1 peer. *Inquiring* behaviour and *repeating* behaviour before year 26 decrease if agents have only one peer, and vice versa if agents that have more than 5 peers.

For the *imitate* and *repeat* behavioural strategies (chosen when agents have a high need satisfaction), the influence of the difference in the number of peers is most pronounced before year 26 (see figure 5.4.2a). *Optimizing* and *inquiring* behavioural strategies (chosen by agents with a low need satisfaction) show a quite steady difference throughout, with the scenarios with more peers showing slightly less difference after year 26, while the scenario with 1 peer showed equal or more difference with the baseline scenario after year 26.

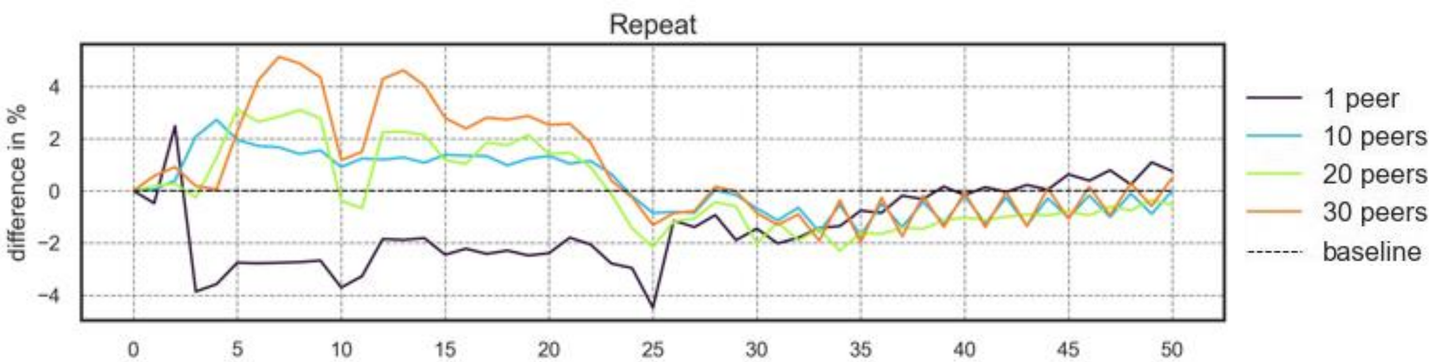

Figure 5.4.2a. The effect of the number of peers on the percentage of agents engaging in the behaviour strategy "repeat".

Need satisfaction

For the existence, personal and overall need satisfaction, differences with the baseline scenario are small, ranging from -1.6 to 1.8 percent. The scenario with 1 peer is most pronounced before year 26, causing a positive difference for the existence and overall need satisfaction, and a negative difference for the personal need. For the social need satisfaction, there is a moderate increase throughout the experiment for all scenarios, see figure 5.4.2b. Noteworthy is that the scenario with 1 peer and the scenario with 30 peers both add 6 percent to the social need satisfaction.

Land use distribution

For the land use distribution, the difference in the number of peers has little impact. Compared with the baseline, the alternative scenarios cause changes between -1,5 and 1,5 percent maximum, with most values between -0.5 and 0.5 percent. After year 26, the changes, already uneven, becomes more abrupt.

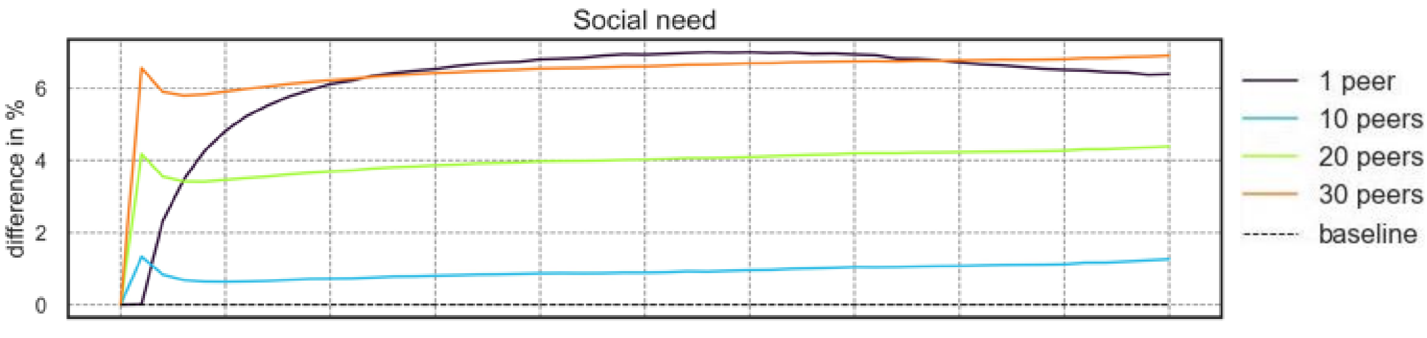

Figure 5.4.2b The effect of the number of peers on the percentage of social need satisfaction.

Weighted peers selection

For the weighted peers selection, six scenarios were compared with the baseline scenario, alternating the weights of the four non-geographical selection criteria versus those of the two geographical selection criteria. Inin the legend, a value of e.g. 0.00/3.00 depicts the value of the non-geographic weights versus the geographic weights. The scenarios were compared with the baseline value where all selection criteria are equal.

Behavioural reporters

For all four behavioural reporters, the scenarios show relatively large, ordered differences, of max -15 to 15 percent compared to the baseline scenario. After year 26, the differences become more uneven. Before year 26, scenarios with more weight to geographical location show much more *repeating* behaviour and much less *imitating* behaviour (see figure 5.4.2c). After year 26, these behavioural strategies, which are both based on high need satisfaction, become closer to the baseline scenario. This indicates a high satisfaction is more impactful for the choice of a behavioural strategy before year 26 than after year 26.

For the low satisfaction strategies, more weight to geographical location impacted the percentage of agents engaging in low uncertainty (*inquiring)* behaviour positively, and impacted those engaging in high uncertainty (*optimising)* behaviour negatively. Uncertainty is partially

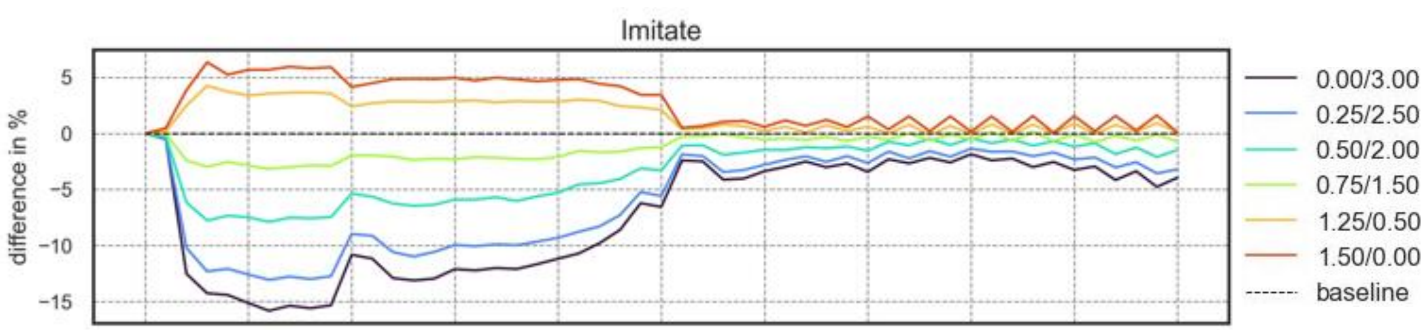

Figure 5.4.2c The effect of non-geographic vs geographic weights on the percentage of agents engaging in the behavioural strategy "imitate"

determined by the similarity with the land use choices of peers. By valuing geographic location more for the selection of peers, less importance is given to the similarity of peers regarding land use selection, land use preference, savings and/or land holdings. Therefore increased geographical weight decreases both the agent's uncertainty *and* agent's social need satisfaction (which is based in part on similarity with peers).

Overall, *repeating* and *inquiring* behaviour is positively influences by an increase of the geographical weights, while *optimizing* and *imitating* behaviour are influenced negatively. The pairing of these behavioural strategies is not based on similarity of need satisfaction or uncertainty.

Need satisfaction

The existence, personal and overall need satisfaction show differences with the baseline scenario that range from -2 to 2 percent. This difference with the baseline scenario is quite even before year 26, but shows much variation after the price crash. For the social need satisfaction, these values are higher throughout the experiment for all scenarios that more heavily weighted closeness of peers, and these values are lower for the scenarios that give more weight to non-geographic factors. The differences of the scenarios compared with the baseline scenario range from -10 to 35 percent. The results of these alternative scenarios are very ordered and very even throughout the experiment.

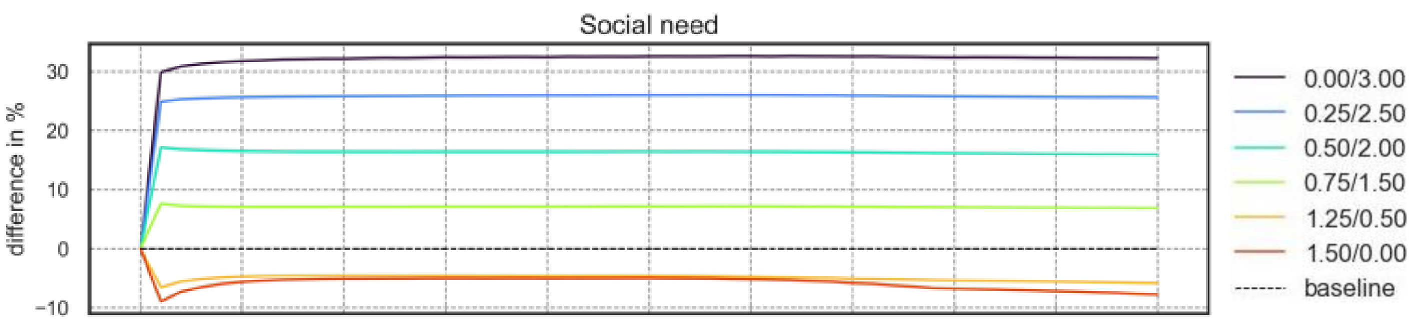

Figure 5.4.2d The effect of non-geographic vs geographic weights on the percentage of social need satisfaction

Land use distribution

In terms of the land use distribution, the land use reporters showed only small differences with the baseline scenario: max values between -2 and 2 percent. Until year 26, the land use reporters showed little impact of the changed weights for the peer selection. After the price crash, all land use reporters showed values that were fluctuating a lot. Noteworthy, after the price crash around year 26, the scenarios with low geographical weights showed more extreme spikes in land use, while scenarios with high geographical weights noticeably showed less extreme fluctuations. These fluctuations were however still relatively small differences compared to the baseline scenario.

Summary of peer selection experiments

The experiments with the number of peers react strongly especially before the 26 year mark. More peers positively influences the percentage of agents engaging in *inquiring* and *repeating* behaviour, and negatively influences *optimizing* and *imitating* behaviour. The scenario with only one peer responds quite sensitive compared with the other scenarios. For the need satisfaction reporters, the social need satisfaction is most impacted, though only moderately. All scenarios (including the 1 peer scenario) have a positive influence on the social need satisfaction. Noteworthy is how the scenario with 1 peer and the scenario with 30 peers together have the largest influence on the social need satisfaction (which is calculated based on similarity (of land use) and superiority (regarding savings) compared to peers). These differences on the behavioural reporters and the need satisfaction reporters does not translate to a pronounced impact on the land use reporters. This is also the case for the experiments with the weighted peer selection.

The weighted peer selection did show large differences for the behavioural reporters. The percentage of agents engaging in high satisfaction behavioural strategies (*repeating* and *imitating)* showed large differences before year 26, compared to the baseline scenario. The low uncertainty strategy (*repeating)* increased, while the high uncertainty strategy (*imitating*) decreased. For the low satisfaction strategies, more weight to geographical location impacted the percentage of agents engaging in low uncertainty (*inquiring)* behaviour positively, and impacted those engaging in high uncertainty (*optimising)* behaviour negatively. This indicates that increased geographical weight decreases both the agent's uncertainty *and* agent's social need satisfaction (which is based in part on similarity with peers). Overall, *repeating* and *inquiring* behaviour is positively influences by an increase of the geographical weights, while *optimizing* and *imitating* behaviour are influenced negatively.

5.4.3 Need satisfaction ratio

For the need satisfaction ratio, seven scenarios were compared with the baseline scenario, alternating the ratio of the Existence, Social and Personal need satisfaction. The ratios shown in the legend of figure 5.4.3a depict the factor used for the Existence need (E), the Social need (S) and the Personal need (P). The scenarios were compared with the baseline value where the Existence need is between 80 and 99, and the Social and Personal need is between 0.5 and 10 (always equal).

Behavioural reporters

For the behavioural reporters, the different ratios of need satisfaction cause a big spike at the beginning of the experiment, especially those where the Existence need satisfaction uses factor 10. This spike evens out, and the differences between the scenarios are smaller and balanced until the price change at year 26. After this year, the strategies of *repeating* and *imitating* increase (the *repeating* strategy up to 30 percent, the *imitating* strategy up to six percent) and the strategies of *optimizing* and *inquiring* decrease (up to -6 and -30 respectively). Thus a lower Existence ratio has a positive impact on behavioural strategies that are chosen by agents with high satisfaction (*repeating* and *imitating*), and have a negative impact on behavioural strategies that are choses by agents with low satisfaction (*optimizing* and *inquiring*). The largest changes are seen for scenarios using factor 10 for the existence need, and for the scenario using factor 45 for existence need, factor 10 for the social need and factor 45 for the personal need.

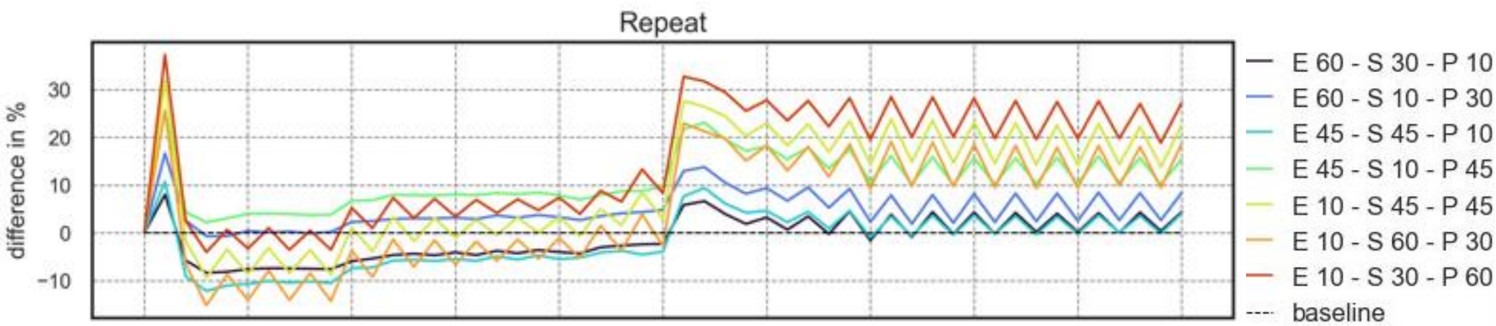

Figure 5.4.3a The effect of different ratios of need satisfaction on the percentage of agents engaging in the behavioural strategy "repeat"

Need satisfaction

For the *social need satisfaction*, the scenarios show little influence: differences with the baseline scenario range from -0.4 – 0.2 percent. Scenarios with a lower importance for Existence need have a positive influence on the *existence need satisfaction* before year 26 (up to 10 percent), however after year 26 there is a dip, a short increase and then *existence need satisfaction* values drop to -10 to -20 percent. The *personal need satisfaction* is positively influenced by a decrease of the importance of Existence need. In scenarios where the Existence need factor is high (45 or 60), the *personal need satisfaction* increases more when the Social need factor is high, than if the Personal need factor is high. The three scenarios where the Existence need factor is 10, cause the biggest gain of *personal need satisfaction* (see figure 5.4.3b). Notably, the scenario when the Social need factor is 60 causes the highest values of *personal need satisfaction*, followed by the scenario with an equal Social and Personal need factor (45), and only then followed by the scenario with a high Personal need factor and a moderate Social need factor (60 and 30 respectively). This indicates a strong influence of the *social need satisfaction* on the *personal need satisfaction*. For the *overall need satisfaction*, there is a big spike at year 1, which balances out quick. The scenarios are relatively stable until year 26, after which there is a sharp increase of *overall need satisfaction*, especially for the scenarios using factor 10 for the Existence need (these have values between 15 and 30 percent).

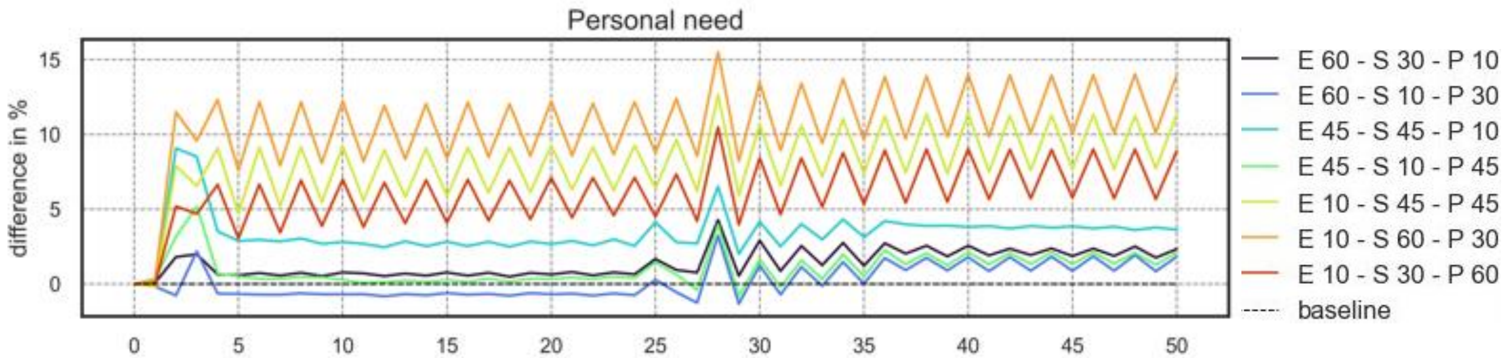

Figure 5.4.3b. The effect of different ratios of need satisfaction on the personal need satisfaction

Land use distribution

The decrease of the importance of the Existence need and the increase of the importance of Social and Personal need, has a positive influence on *cleared field* and *collaborative* land use. *Individual* and *forest cover* land use is impacted negatively by a devaluation of the Existence need importance. The difference between the baseline scenario and the alternative scenarios gradually grows to a max value of 10 percent around the 26st year. After this, the values spike, and the *cleared field* and *collaborative* land use increase up to 20 and 15 percent, respectively. The *individual* and *forest cover* land use decrease to -15 and -20 percent (respectively).

Summary of need satisfaction ratio experiments

For the behavioural reporters, lower Existence ratios have a positive impact on behavioural strategies that are chosen by agents with high satisfaction (*repeating* and *imitating*), and a negative impact on behavioural strategies that are choses by agents with low satisfaction (*optimizing* and *inquiring*). This indicates agents become more satisfied if the Existence need ratio is lower. This is also observed for the need satisfaction reporters. The overall need satisfaction decreases for most scenarios before year 26, but increases greatly after year 26. Notably, the highest values of *personal need satisfaction* are scenarios with a low Existence need satisfaction, a high Social need satisfaction and a moderate Personal need satisfaction. This indicates a strong influence of the *social need satisfaction* on the *personal need satisfaction*, while the *social need satisfaction* values are barely influenced by the different satisfaction ratios. For the land use reporters, lower Existence need ratios have a positive influence on *cleared field* and *collaborative* land use. *Individual* and *forest cover* land use is impacted negatively by a lower Existence need importance.

6 Conclusion

The aim of this research was to provide a quantitative evaluation of the robustness of the model parameters and the system assumptions of the LUSES-model, with special attention to the implementation of the Consumat framework. This aim was achieved by answering the four research question.

The first research question was "what are the most important concepts to understand a quantitative evaluation of the LUSES model?". Two types of validation were found to be important: the validation of model output (providing insight into the model by exploring parameter settings and the model output) and internal validation (exploring consistency of the model with the model rules and/or assumptions). These two types of validity can be assessed by sensitivity analyses and by experiments with scenarios. Suitable sensitivity analysis are the One-factor-at-a-time (OFAT) local sensitivity analysis, complemented by a global sensitivity analysis such as the Sobol' analysis.

The second research question was "how to adapt the LUSES model to perform a quantitative evaluation?". To prepare the LUSES model for a quantitative evaluation (using the OFAT analysis, Sobol' analysis and scenario experiments), a method for data extraction was set up. Using the PyNetlogo library, the process of data extraction in NetLogo could be automated through Python. For this purpose, Python scripts were written and the NetLogo model was adapted. Additionally, a variance analysis was performed to assess the necessary amount of runs for variance stability.

The third research question was: "how to assess the robustness of the model output due to parameter settings and their interactions?". This research question was answered using an OFAT analysis and a Sobol' analysis. The OFAT analysis showed that all variables react sensitive to the price shift after year 24-26: this causes stronger reactions to parameter changes and much more fluctuations. This shows the model reacts sensitive to a decline of crop prices if the price has been stable in the years prior to the price drop. In addition to this, the social need reporter is barely affected for all variables. The Aspiration parameter has a large impact on all reporters, and its more extreme parameter values showed a lot of fluctuation. The Cognitive variable also showed a lot of fluctuation between year 24 and 36 for all reporters. The Uncertainty variable had a large impact on the behavioural reporters in particular. For the Existence, Social and Personal need variables, parameter values that are further from the average have a lot of fluctuations after year 26.

The Sobol' analysis includes interaction effects in the analysis of the influence of parameter changes on the variance of the model variance. All variables have moderate to large influences on the reporters if interaction effects are included. Interesting are the change of the Aspiration and

Existence need variable for the behavioural reporters, which have the lowest influence without interaction effect and the highest influence including interaction effects. For the social need satisfaction reporter, without interaction effects almost no variance is explained for all variables, but when including interaction all variables have a high influence on the reporter. For the land use reporters and the existence need and personal need satisfaction, the Existence need variable explains very little variance without interaction effect – with interaction a very high amount is explained. Some of the results of the Sobol' analysis first indices (without interaction effects) are striking when compared with the OFAT analysis, since they contradict the OFAT results.

The fourth research question was: "what impact can be expected by change of 'system' assumptions?". This was assessed by running scenarios with alternative system assumptions. Experiments with the cognitive function showed a longer memory impacts the likelihood of agents having both low satisfaction and low uncertainty, or both high satisfaction and high uncertainty. Agents with a long memory also show a slower decline of need satisfaction (overall and existence) after sharp price declines. The removal of cognitive decay causes agents to have a higher need satisfaction.

The peer selection scenarios impacted the behavioural reporters and the need satisfaction reporters; however, it did not influence the land use reporters. Increasing the number of peers increases *inquiring* and *repeating* behaviour, and decreases *optimizing* and *imitating* behaviour. All scenarios positively influence the social need satisfaction, and the 1 peer scenario and the 30 peers scenario have the largest influence. For the weighted peer selection, increased geographical weight decreased the agent's uncertainty and increased the agent's social need satisfaction.

For the need satisfaction ratios, agents are more satisfied with a lower Existence need ratio. The need satisfaction ratios indicate a strong influence of the *social need satisfaction* on the *personal need satisfaction*, since the highest values of *personal need satisfaction* are gained in scenarios with a low Existence need satisfaction, a high Social need satisfaction and a moderate Personal need satisfaction. In some instances, change of the need satisfaction ratio, the number of peers or the cognitive function *outside* the bounds of the baseline settings caused unexpected results. These results were no modelling error but resulted from rules of the computational model. These results, however, do not reflect reality.

To conclude, this quantitative evaluation of the robustness of the model parameters and the system assumptions of the LUSES-model showed a sensitivity to the price changes. Additionally, the OFAT analysis showed a strong reaction to changes of the aspiration variable, however the Sobol' analysis of the output variance including interaction effects showed the existence need satisfaction variable was most influential on the output variance. The social need variable was not responsive to parameter changes of the main variables, however, changes of the number of peers or the weights of the peer selection had a large influence on this variable. No abnormalities were found that could not be explained by taking a closer look at the model logic, though the analysis of the system assumptions showed the model should not be used with settings that deviate from the baseline settings or parameter bounds that were tested in the OFAT analysis.

7 Discussion

In this research, the robustness of the parameters of the LUSES model was evaluated, including analysis of interaction effects. In addition to this, the system assumptions were assessed by analysing alternative scenarios. To test the robustness of the parameters, six main parameters were selected for an OFAT analysis and a Sobol' analysis. The system assumptions analysis looked at alternative scenarios of the cognitive function, the selection of peers and the need satisfaction ratio. The LUSES model is very elaborate, and there are many variables and parameters to choose to assess. In this research the main parameters were tested, as well as the system assumptions that were most relevant (based on the LUSES model, the Consumat framework and literature).

Both the OFAT and the systems analysis showed a stronger sensitivity of the model around large changes in land use prices. The parameter changes reacted especially sensitive around time step 26, after extreme changes of land use 3 prices. This sensitivity is due to the cognitive effort variable, which causes agents to react extremely to negative shifts of prices that were stable for a long time. For the OFAT analysis, the response to this price change was especially visible with parameter values that were further from the average parameter value. The Existence, Social and Personal need variables showed a lot of fluctuations after year 26 for parameter values that are further from the average. The Cognitive variable also reacted strongly to price changes, showing strong fluctuations specifically between year 24-36, for all parameter values. This indicates the dramatic negative price shift caused instability for many time steps after the prices dropped.

Another noteworthy result of the OFAT analysis is how the social need reporter is barely affected for all variables during all time steps. This is interesting when compared with the Sobol' analysis, which shows that the social need reporter is not influenced *directly* by any variable, however all variables influence the social need reporter indirectly. For the systems analysis, only scenarios with different weights for the peer selection or a different number of peers cause noteworthy changes to the social need reporter. This can be explained by the fact that the social need reporter is determined by similarity and superiority with peers, therefore the variables only influence the social need satisfaction indirectly. However, the question remains to what extent the social need satisfaction adds to the model, since the response to (extreme) parameter changes is so small. Since the social need reporter shows the average of all agents (macro level), an analysis of the social need satisfaction on agents level (micro level) would be necessary to draw a conclusion on the contribution of the social need satisfaction to the model as a whole. Thinking of An (2012), who stresses the importance of the social network in psychosocial and cognitive decision-making models, it is worth examining why no changes of social need satisfaction are visible on the macro level of the model.

For the Sobol' analysis, all five variables were influential for each reporter when taking into account interaction effects. This analysis does not specify the amount of variance that is explained by a variable. It does, however, emphasize the complexity of the LUSES model by showing how all variables influenced almost each reporter in some way – which is exactly what makes complex systems so difficult to analyse. The Existence need specifically showed a lot of influence through interaction effects on the land use reporters and the overall and personal need satisfaction. Since this variable is used for many parts of the model, this is not surprising. Some of the results of the Sobol' analysis first indices (without interaction effects) are striking when compared with the OFAT analysis, since they contradict the OFAT results.

The system assumptions analysis showed results that were in line with the way the model was implemented, and with the conceptual ABM. The model responded as expected for most scenarios, though the results were not necessarily a reflection of what would logically happen in real life, nor a reflection of the TyL case study (Speelman et al., 2014). The model produced surprising results in the scenario with the number of peers. The social need satisfaction was greatly increased by both the 1 peer and the 30 peers scenario. This can be brought back to the calculation of the social need satisfaction, which is based on the similarity and superiority compared to peers. Another unexpected result was encountered for the need satisfaction ratio. There it was observed how the personal need satisfaction is the highest when the Existence need ratio is low, and the Social need ratio is higher than the Personal need ratio. This shows again how interaction effects can influence the model outcomes. Overall, the system analysis confirmed the model works as intended and as expected, though it also shows that the model should be carefully validated before it can be used with values other than the baseline parameters: the use of parameter settings that deviate from the baseline settings should be attempted with caution.

In terms of the reliability of the results, both the OFAT analysis, Sobol' analysis and analysis of scenarios are commonly used for similar research purposes and are suitable to use to perform quantitative ABM evaluation. The variance analysis was not performed specifically for the systems analysis, which means the results of the systems analysis that used parameters outside the baseline parameter bounds could have a slight deviation compared to a similar experiment. These differences are however likely to be very small (<0.5 percent). A more important limitation of the research is that the Cognitive variable was not taken into account for the Sobol' analysis. The assessment of the influence of this variable would have been insightful, partly because this variable is adapted from the Consumat framework. This means certain interaction effects (which might explain some of the differences between the Sobol' and the OFAT analysis) could not be studied for the Sobol' analysis. Because of the nature of complex systems, a variance analysis such as the Sobol' analysis or another type of global sensitivity analysis is necessary for proper model evaluation, since these take into account interaction effects. The lack of additional analysis including the Cognitive variable is therefore unfortunate but could not be helped due to time constrains (the analysis took over 90 hours to run). Time constraints also prevented from running an analysis with a higher sample size, to improve the confidence bounds. For the current Sobol' analysis, not all results fell within the 0.05 margins.

The sensitivity of the model to the price changes had a big influence on the model variance in all three analyses. Using different, more even crop prices might give more context to sensitivity of the parameters, since the land use prices had such a big influence on the model variance. Testing the model by using the TyL land use prices is an essential part of testing the variance of the OFAT model output, however in addition to this it might be insightful to see how the model responds if there are less abrupt or less extreme land use changes.

In a broader sense, this thesis illustrates one of the main difficulties with ABM analysis. This analysis, for the most part, looked at the impact of the main six variables of the LUSES-model on 16 output variables. To communicate an extensive analysis of the model in a way that is both understandable and to the point has been challenging. This is a know difficulty with ABMs (Müller et al., 2013; Lorscheid et al., 2012).

There are still many possibilities for further exploration of the model, but a thorough model evaluation has been provided within this research. As a last measure to ensure the validity of the model and the theory behind the model, it is recommended by De Smith (2018) and Edmonds and Hales (2005) to replicate the model in another modelling language or to re-build the model from scratch. This method, though time-intensive, is suggested to provide a final measure of validity. Alternatively, this can be combined with the adaptation of the LUSES model to fit another case-study (of a similar, smallholder farming community). Doing so can provide insight into the generalizability of (aspects of) the LUSES model. This also provides an opportunity to generalize the application of the Consumat framework in smallholder farming ABMs, taking the LUSES model as a starting point.

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9 Appendix 1.

Table of Content of the ZIP file / USB that accompanies the thesis report:

Report	Final_Thesis_GPDees.pdf Final_Thesis_GPDees.docx
Midterm presentation (PPT)	Midterm_Presentation_GPDees.pptx
Datasets	Folder OFAT_data Folder Sobol_data Folder SysA_data Folder Variance_data
Figures	Folder OFAT_figures Folder Sobol_figures Folder SysA_figures
Scripts	Code_Analysis_OFAT&SysA.ipynb Code_Analysis_Sobol.ipynb Code_Variance.ipynb Code_Visualization_OFAT&SysA.ipynb Code_Visualization_Sobol.ipynb
Netlogo code	LUSESmodel_6.0.4_adapted.nlogo LUSESmodel_Original.nlogo