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An Agent-based Model of Wood Markets in Switzerland

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The Faculty of Business, Economics and Informatics of the University of Zurich hereby authorizes the printing of this dissertation, without indicating an opinion of the views expressed in the work.

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Abstract

The sustainable potential of the resource wood is currently not tapped in Switzerland, as the amount of wood harvested is smaller than the amount that regrows. There are many possible reasons for this, such as the fine-grained supply structure: in Switzerland, there are approximately 250'000 private forest owners who own on average a forest area of approximately 1.5 ha. This makes the sale of wood financially not very attractive for them. Also, public forest enterprises in Switzerland manage rather small forest areas compared to other European countries. Personal relationships play an important role in the Swiss wood markets, so potential business transactions are not solely evaluated based on economic criteria. In alpine areas, harvesting wood is associated with high costs. At the same time, wood prices are largely determined by international wood prices, which comes along with a dependency of the Swiss wood markets on the exchange rate EUR-CHF.

Computer simulation is one possibility to examine how these and other characteristics of the Swiss wood markets influence the availability of wood. The development of a computer model allows the simulation of different scenarios in order to gain insights that are otherwise difficult to gain. For example, the impact of the market participants' decision-making behavior on the quantities of wood available on the market can be investigated, i.e. which market participants can get what amount of wood at what time, and what prices they have to pay for it. The influence of the market structure, such as the existence of intermediaries or potential consequences of combining smaller forest enterprises to larger ones, can also be examined.

The characteristics of these markets make agent-based modeling a promising approach to simulate these markets. In an agent-based model (ABM), a system is modeled by describing its constituting entities, referred to as agents. In the given case, these agents represent the market participants. Each agent can be attributed with individual characteristics and behavior. When these agents are simulated, the aggregate behavior can be observed, e.g. the quantities traded on the market and the corresponding prices. This aggregate behavior *emerges* from the many interactions and decisions of the individual agents. The behavior of the entire system is often unpredictable, sometimes even counterintuitive, if only the behavior of the individual elements of the system is considered. It is only the interplay of these elements which makes emergent phenomena observable. The ability to observe emergent phenomena is a central strength of agent-based simulation. The bottom-up description of the system also allows the modeling of

the structures and relationships at the level of individual market participants. These play an important role in the Swiss wood markets.

This dissertation was conducted according to the design science research paradigm. Concerning the specific requirements of this thesis, this means that the aim was to create a model that represents the Swiss wood markets with sufficient accuracy, so that it can be used to gain new insights into these markets.

This cumulative PhD thesis comprises four peer-reviewed journal publications, three of them are already published, the fourth is submitted. Each of these publications deals with a central step towards the overall goal: the first shows a simplified agent-based model of the sawlogs and energy wood market in the canton of Aargau. Simple scenarios demonstrate the suitability of the approach, but also reveal issues which need further research. The second publication focuses on how discrete choice experiments can be used to enhance the empirical foundation of the agents' decision-making behavior. The third publication describes the validation of the model, which now represents the sawmill, energy wood and industrial wood markets (all three further divided into one market for softwood and one for hardwood). Validating the model is an important prerequisite to use it for scenario analysis. The last publication in this thesis finally shows the simulation and analysis of various politically relevant scenarios. This includes an analysis of how the market is influenced by the presence of intermediaries or by the intensity of profit orientation of forest owners.

The developed model can be parameterized for different Swiss regions in order to simulate the regional wood markets. The necessary empirical data was gathered for the cantons of Aargau, Bern and Grisons. Currently, the model is parameterized and validated for the canton of Grisons. Particularly the last publication demonstrated that the model can be used to provide insights into these markets by simulating and analyzing different scenarios. However, the model itself is not the only contribution of this thesis. On the one hand, to develop this model, several problems had to be solved that could be of interest to modelers of other markets. One example is the problem of defining the geographical model boundaries in a market that is heavily influenced by the surrounding international markets. On the other hand, the creation of such a model already provides many valuable insights into the markets under study, since knowledge about them must be gathered and interpreted. This makes the journey a considerable part of the reward.

Zusammenfassung

Das nachhaltige Potential der Ressource Holz wird aktuell in der Schweiz nicht ausgeschöpft, da weniger Holz geerntet wird, als nachwächst. Dafür kommen viele Gründe in Frage, beispielsweise die feinkörnige Angebotsstruktur: in der Schweiz gibt es ca. 250'000 Privatwaldbesitzer, die durchschnittlich eine Waldfläche von ca. 1.5 ha besitzen, was für diese den Holzverkauf finanziell nicht sehr attraktiv macht. Auch die öffentlichen Forstbetriebe bewirtschaften im Vergleich zu anderen europäischen Ländern eher kleine Flächen. Persönliche Beziehungen spielen eine wichtige Rolle auf den Schweizer Holzmärkten, was dazu führen kann, dass mögliche Holzverkäufe nicht alleine aufgrund ökonomischer Kriterien beurteilt werden. In alpinen Gebieten ist die Ernte zudem mit hohen Kosten verbunden. Gleichzeitig werden die Schweizer Holzpreise weitgehend durch die internationalen Holzpreise bestimmt, was auch eine Abhängigkeit des Holzmarktes vom Wechselkurs EUR-CHF zur Folge hat.

Computersimulation ist eine Möglichkeit, um zu untersuchen, welche dieser und weiterer Eigenschaften der Schweizer Holzmärkte welchen Einfluss auf die Verfügbarkeit von Holz haben. Die Erstellung eines Computermodells ermöglicht die Simulation von unterschiedlichen Szenarien, um damit Erkenntnisse zu gewinnen, die auf andere Weise nicht gewonnen werden können. So können zum Beispiel die Auswirkungen des Entscheidungsverhaltens der Marktteilnehmer auf die auf dem Markt verfügbaren Holz-mengen untersucht werden, d.h. welche Akteure zu welcher Zeit wie viel Holz erhalten können, und welche Preise sie dafür bezahlen müssen. Auch der Einfluss der Marktstruktur, wie zum Beispiel das Vorhandensein von Intermediären oder mögliche Auswirkungen von Zusammenschlüssen von kleineren Forstbetrieben, können damit untersucht werden.

Ein agentenbasiertes Modell (ABM) eignet sich aufgrund der genannten Eigenschaften dieser Märkte besonders, um sie zu modellieren. In einem ABM wird ein System modelliert, indem die einzelnen Einheiten, die dieses System bilden, beschrieben werden. Diese Einheiten werden Agenten genannt und entsprechen im vorliegenden Fall den einzelnen Marktteilnehmern. Jedem Agenten können dabei individuelle Eigenschaften und Verhaltensweisen zugewiesen werden. Werden diese Agenten dann simuliert, kann das aggregierte Gesamtverhalten beobachtet werden, also zum Beispiel welche Mengen insgesamt auf dem Markt gehandelt werden und zu welchen Preisen. Dieses Gesamtverhalten *emergiert* aus den vielen Interaktionen und Entscheidungen der einzelnen Agenten. Das Verhalten des Gesamtsystems ist oft nicht vorhersehbar, und widerspricht teilweise sogar der Intuition, wenn ausschliesslich das Verhalten der ein-

zelnen Elemente dieses Systems betrachtet wird. Erst durch das Zusammenspiel dieser Elemente können emergente Phänomene auf Ebene des Gesamtsystems beobachtet werden. Die Möglichkeit des Beobachtens von emergenten Phänomenen ist eine zentrale Stärke der agentenbasierten Simulation. Durch die Bottom-up-Beschreibung des Systems können ausserdem die Strukturen und Beziehungen auf der Ebene der einzelnen Marktteilnehmer, die auf den Schweizer Holzmärkten eine wichtige Rolle spielen, besonders gut abgebildet werden.

Diese Dissertation wurde anhand des Design Science Research Paradigmas durchgeführt. In Bezug auf die konkrete Problemstellung der vorliegenden Arbeit heisst das, dass es das Ziel war, ein Modell zu erstellen, das die Schweizer Holzmärkte in einer ausreichenden Genauigkeit abbildet, damit es dazu genutzt werden kann, neue Erkenntnisse über diese Märkte zu gewinnen.

Diese kumulative Dissertation umfasst vier peer-reviewte Journal-Publikationen, von welchen drei bereits veröffentlicht sind, die letzte befindet sich im Review-Prozess. Jede dieser Publikationen behandelt einen zentralen Schritt auf dem Weg zum Gesamtziel: Die erste zeigt ein vereinfachtes ABM des Rundholz- und Energieholzmarktes des Kantons Aargau. Einfache Szenarien zeigen die Funktionstauglichkeit des Ansatzes, jedoch auch Punkte, die noch verbessert werden müssen. Die zweite Publikation zeigt, wie Choice Experimente genutzt werden können, um das Entscheidungsverhalten der Agenten empirisch besser abzustützen. Die dritte Publikation zeigt schliesslich die Validierung des Modells, das nun die Märkte für Sägeholz, Energieholz, und Industrieholz (alle drei jeweils noch unterteilt in einen Markt für Nadelholz und einen für Laubholz) abbildet. Diese Validierung ist eine wichtige Voraussetzung, um das Modell anschliessend zur Szenarienanalyse nutzen zu können. Die vierte Publikation dieser Arbeit zeigt schliesslich die Simulation und Analyse verschiedener politisch relevanten Szenarien. Dies umfasst u.a. eine Analyse der Auswirkungen auf den Markt durch die Präsenz von Intermediären oder durch die Ausprägung der Profitorientierung von Waldbesitzern.

Das erstellte Modell kann für verschiedene Regionen der Schweiz parametrisiert werden, um die Holzmärkte dieser Regionen zu simulieren. Die dazu notwendigen empirischen Daten wurden für die Kantone Aargau, Bern und Graubünden erhoben. Aktuell ist das Modell für den Kanton Graubünden parametrisiert und validiert. Insbesondere die letzte Publikation hat gezeigt, dass das Modell zur Erkenntnisgewinnung genutzt werden kann, indem Szenarien simuliert und analysiert werden. Das Modell selbst ist jedoch nicht das einzige Ergebnis der vorliegenden Arbeit: Einerseits mussten bei der Erstellung des Modells einige Probleme gelöst werden, die auch für Modellierer anderer Märkte interessant sein können. So zum Beispiel das Problem der geographischen Modellabgrenzung auf einem Markt, der stark von den umliegenden, internationalen Märkten beeinflusst wird. Andererseits liefert bereits die Erstellung eines solchen Modells viele wertvolle Erkenntnisse über die abzubildenden Märkte, da Wissen über diese gesammelt und geordnet werden muss. Der Weg zum Ziel, ein solches Modell zu erstellen, ist also bereits ein beträchtlicher Teil des Ziels selbst.

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Synopsis

1.1 Introduction

In this thesis, an agent-based model (ABM) of Swiss wood markets was developed. Why is it necessary to develop a model of these markets? What makes agent-based modeling the appropriate modeling approach? And why is this topic worth a PhD thesis in computer science?

The sustainable potential of wood as a natural resource is currently not tapped in Switzerland, and the wood markets in Switzerland are sometimes deemed inefficient. Having a computer model of these markets offers the possibility to conduct experiments *in silico* – experiments that normally cannot be conducted in reality. Such experiments are conducted by using the model to simulate different scenarios and analyzing their output. If-then-analyses can be a step towards a better understanding how these markets work, and the analysis of politically relevant scenarios can provide helpful insights prior to the implementation of political measures. Gaining a better understanding of the internal processes of these markets and the behavior of the market participants was the main requirement given by the National Research Foundation, which funded this thesis in the context of the National Research Program NRP66 (SNF, 2010).

Agent-based modeling is a simulation paradigm that models a system bottom-up, by modeling its constituting units, named agents. This bottom-up approach often allows a natural description of the system: in the case of a market for example, the agents represent the market participants. When these agents are simulated, it can be observed how traded quantities and prices emerge from the many individual decisions of the market participants. The possibility to observe emergent phenomena on any level of aggregation is one of the core strengths of agent-based modeling. The characteristics of the Swiss wood markets make agent-based modeling a promising modeling approach to investigate these markets (cf. Troitzsch, 2012). There is for example the market for sawlogs, which are the main product on the Swiss wood markets. This market is characterized by a very large number of small suppliers (>250'000), and a small number of large demanders. The product has, in relation to its volume, a small value: the price of one cubic meter of wood is approximately CHF 100. A comparison with other products, e.g. one cubic meter of gasoline, which has a value of approximately CHF 1'500¹, makes it obvious that transportation costs are a considerable cost item.

¹Under the assumption of a price of CHF 1.50 per liter at a gas station in Switzerland

Because the transportation of sawlogs is expensive, a short geographical distance between supplier and demander is crucial. Moreover, wood is a heterogeneous product which differs e.g. in quality. Quality and exact size of a sawlog are often measured in the sawmills, meaning that the wood supplier has to trust the sawmill that quality and size are measured correctly. This makes trust between contract partners an important prerequisite for the conclusion of contracts. Wood is a scarce resource within the meaning of being available only to a limited quantity per time and region, especially if it is harvested in a sustainable way (without e.g. forest clearances) as it is the case in Switzerland. Finally, there are by-products accumulated when sawlogs are harvested and processed, which are also valuable: energy wood that can be used for heating purposes, or industrial wood that can be used for paper production. All these characteristics make agent-based modeling a promising modeling approach for the markets under study. The possibility of i.) modeling each market participant individually, ii.) setting the market participants in a geographical context to model the transportation distances, iii.) modeling the mutual trust between market participants, iv.) specifying the temporal and regional availability of the resource, and v.) modeling the interdependence between the main product and the by-products, are all aspects that can be elegantly modeled by using an agent-based approach.

The reason why the development of an agent-based model of these markets is worth a PhD thesis in computer science is threefold. First, the development of this model offers the opportunity to explore several issues which can be of interest for modelers of other markets. There is for example the combination of agent-based modeling with discrete choice experiments, a preference elicitation method based on theories of human decision-making (cf. section 3.4.1). There are several studies where these two approaches have been combined (cf. section 3.2), but so far a description of a precise method has not been published in the literature. There are also certain unsolved challenges in the first version of the model (described in chapter 2), whose solutions might be interesting for modelers of markets with similar characteristics. Such challenges are for example an appropriate modeling of model-boundaries, or the modeling of transportation routes. The second reason is the need for a model which is able to simulate and investigate the markets under study, for example to simulate politically relevant scenarios prior to their implementation, or to investigate the influence of intermediaries on traded quantities and prices. The third reason is that developing a highly descriptive model (cf. KIDS strategy of Edmonds and Moss, 2004) that must be able to simulate large quantities of agents in a reasonable time, while also being flexible concerning model adaption and model evaluation, requires the application of state-of-the-art software-engineering principles.

These reasons and the challenge of designing and implementing a model fulfilling all the mentioned requirements make the design science research paradigm the method of choice to guide the research of this thesis. This paradigm will be introduced in section 1.2, after the research questions are concretized. Section 1.3 summarizes the published articles constituting this cumulative thesis. Section 1.4 discusses limitations of the work, while section 1.5 shows possible future research directions. Section 1.6 concludes the synopsis. The subsequent chapters show the contributions as they were published (or submitted) in the scientific journals.

1.2 Research Questions

The goal of this thesis is to develop a model which is able to improve the understanding of the Swiss wood markets. Particularly, it should help to find answers to the following questions that were defined in the research proposal of this thesis (Holm, 2014):

1. How can the principles of actor behavior in these markets be described?
2. How does the actor behavior influence the availability of wood?
3. How does the market structure influence the Swiss wood markets?

These research questions were concretized to a set of scenarios which the model should be able to simulate. Each of these scenarios addresses a different question (Holm, 2014):

- **Domat/Ems case.** What behavioral or structural conditions have led to the bankruptcy of the large-sized sawmill in Domat/Ems, and how could it have been avoided?
- **Market Entry/Exit of bulk consumers.** How does the market entry or exit of bulk consumers influence the wood market?
- **Impact of bundling organizations on the market.** How do bundling organizations influence the supply of wood to the market? Do they influence the availability of wood?
- **Motivation of inactive suppliers.** How can private forest owners, who do not harvest wood and sell it on the market, be motivated to do so? Are subsidies an option?
- **Having binding contracts instead of lose agreements.** How does the nonexistence of binding contracts influence the market?

The challenge of the requirement to simulate these scenarios is to design a model which represents the markets under study adequately while being valid enough to be used for policy analysis. This is a design problem: it requires, for example, the definition of the relevant agents, an adequate interaction scheme, the elicitation of the preferences of the market participants to model a realistic decision behavior, and the gathering of further empirical data to parameterize the model. Then, the resulting model has to be validated thoroughly so that it finally can be used for the defined purpose. To solve this design problem, the research in thesis is based on and guided by the design science research (DSR) paradigm, which can be defined as follows (Hevner and Chatterjee, 2010, p.5):

"Design science research is a research paradigm in which a designer answers questions relevant to human problems via the creation of innovative artifacts, thereby contributing new knowledge to the body of scientific evidence. The designed artifacts are both useful and fundamental in understanding that problem."

The design science research paradigm differs from the traditional behavioral science paradigm. While behavioral science wants to find the truth, starting with a hypothesis

that should be proven or disproven, the design science research approach is *"a problem-solving paradigm whose end goal is to produce an artifact which must be built and then evaluated"* (Hevner and Chatterjee, 2010). DSR is perfectly suited as a guideline for the classical modeling and simulation approach, which assumes that the model builder proceeds in a cycle of developing a conceptual model, implementing it, simulation and evaluation (Page et al., 1991). Hevner et al. (2004) specify seven guidelines *"for conducting and evaluating good design science research"*:

- **Guideline 1: Design as an Artifact.** Design research must produce a viable artifact in the form of a construct, a method, or an instantiation.
- **Guideline 2: Problem relevance.** The objective of the design science research is to develop technology-based solutions to important and relevant business problems.
- **Guideline 3: Design evaluation.** The utility, quality, and efficacy of a design artifact must be rigorously demonstrated via well-executed evaluation methods.
- **Guideline 4: Research contributions.** Effective design science research must provide clear and verifiable contributions in the areas of the design artifact, design foundations, and/or design methodologies.
- **Guideline 5: Research rigor.** Design science research relies upon the application of rigorous methods in both the construction and evaluation of the design artifact.
- **Guideline 6: Design as a search process.** The search for an effective artifact requires utilizing available means to reach desired ends while satisfying laws in the problem environment.
- **Guideline 7: Communication of research.** Design science research must be presented effectively to both technology-oriented and management-oriented audiences.

In the research proposal of this thesis, it was stated how each of these guidelines will be addressed. A comparison between these statements and the actual outcome of this thesis regarding these guidelines is presented in Appendix 1.A.

1.3 Contributions

This cumulative PhD thesis comprises four journal papers. Three papers have already been published, one has been submitted. The following sections outline these papers and show how they relate to each other. Their relations to scientific contributions from other authors are summarized in the papers themselves.

Note that the terminology in the published versions of the first two papers is slightly different than in the others. The terms *roundwood* and *wood fuel*² used in the first two

²In the paper described in chapter 2, the term *wood fuel* is also meant to include industrial wood, which is in the later versions of the model an assortment on its own.

papers have been replaced in the subsequent papers by the terms *sawlogs* and *energy wood*, as these terms describe more precisely what has been modeled actually.

1.3.1 Simulation of a Swiss wood fuel and roundwood market: An explorative study in agent-based modeling

Kostadinov, F., Holm, S., Steubing, B., Thees, O., & Lemm, R. (2014). Simulation of a Swiss wood fuel and roundwood market: An explorative study in agent-based modeling. *Forest Policy and Economics*, 38, 105-118.

In this paper, a first version of the model is presented. It represents the sawlogs and energy wood market (therein referred to as roundwood and wood fuel market) in the canton of Aargau in Switzerland. Two sets of scenarios were simulated to show the potential of using an agent-based model to simulate these markets. In one set of scenarios, parameters concerning the supply side of the market were changed (the amount of wood forest owners are allowed to harvest). In the other set parameters concerning the demand side (the number of demanders in the market) were modified. The model was able to reproduce well-known economic characteristics (for example that a reduced supply leads to higher prices) and provided insights into the optimal number of demanders in the market from the perspective of different stakeholders. The paper thereby shows the potential of the approach of using an agent-based model to explore the Swiss wood markets. The paper also revealed some unsolved challenges and showed where further research is necessary. Namely the following issues were identified:

- A better empirical foundation of the model, especially regarding the decision-making process, the decision behavior, and the interaction pattern of the market participants.
- A more realistic modeling of the transportation routes. For a good with a low price per volume, transportation costs account for a large part of the total costs. This makes an adequate modeling of transportation routes crucial. In this first paper, Euclidean distances between seller and buyer were used to calculate transportation costs, which is especially problematic in mountainous terrain³.
- A better definition of the model boundaries: a significant amount of wood produced in the modeled region AG (the canton of Aargau in Switzerland) is processed by demanders outside of AG, while demanders inside AG may also buy wood from suppliers outside AG. Therefore, using the geographical boundaries of AG as model boundaries, as done in this first paper, leads to a distortion of supply and demand. Additionally, agents close to the border have less potential business partners in their neighborhood, and therefore have a competitive disadvantage.

³This can be illustrated by the example of two municipalities in the canton of Grisons, one of this thesis' main study region: between the municipalities Arosa and Davos, the Euclidean distance is approximately 11 km, the shortest path on the road about 85 km!

These challenges, together with the research questions defined in section 1.2, substantiate and motivate the subsequent papers. Chapter 2 presents the paper as it is published in the journal *Forest Policy and Economics*.

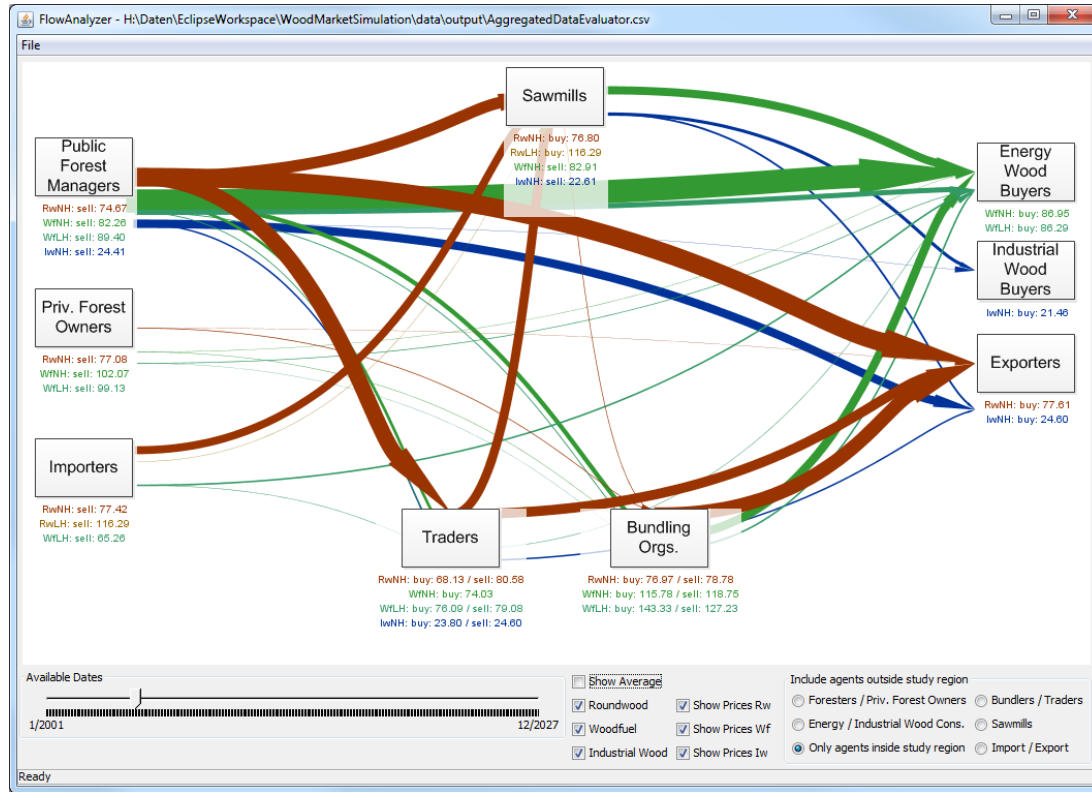


Figure 1.1: **FlowAnalyzer**. This tool was developed by the author of this thesis to facilitate a simple visual analysis of resource flows between the agent types. It reads the CSV-files (comma-separated values) generated during a simulation and allows, with the slider on the bottom left of the window, to see the resource flows and prices paid for each simulated time step. Such diagrams, in which the width of an arrow is proportional to the quantity of resource flow (in this case traded amounts), are also known as Sankey diagrams. Brown arrows represent sawlogs, green arrows energy wood, blue arrows industrial wood. An earlier version of this tool was used to generate Figure 2.4 in the paper presented in chapter 2.

1.3.2 Enhancing Agent-based Models with Discrete Choice Experiments

Holm, S., Lemm, R., Thees, O., & Hilty, L.M. (2016). Enhancing Agent-based Models with Discrete Choice Experiments. *Journal of Artificial Societies and Social Simulation*, 19(3), 3. doi:10.18564/jasss.3121

In this paper, the approach of parameterizing an agent-based model with empirical data from discrete choice experiments (DCEs) is described. The most important changes of the model compared to the previous paper are the following:

- Now, three markets were modeled: the markets for sawlogs, energy wood, and industrial wood. There were also some new agent types added compared to the previous paper. However, the focus of the simulation results lies on the sawlogs market and the two most important agent types therein: public forest managers and sawmills. They are used to evaluate the successfulness of the presented approach.
- Transportation costs are now no more calculated by the Euclidean distance between buyer and seller, but by an explicit modeling of road routes (cf. Figure 1.2).

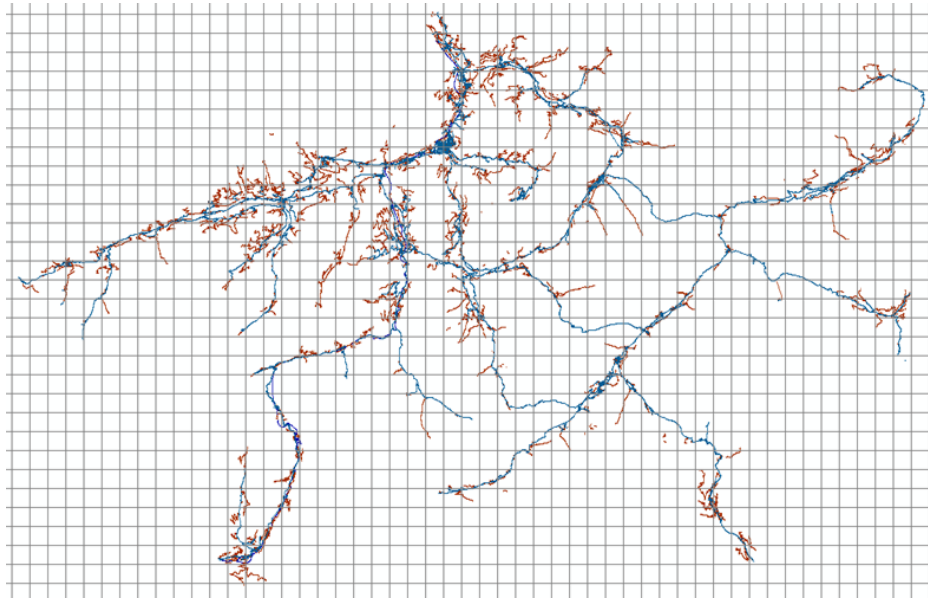


Figure 1.2: **Modeling of transportation routes.** To model transportation routes realistically, the road network of the modeled region was overlaid with a regular grid with a horizontal and vertical Euclidean distance of 3km between the nodes. For each node in the grid, the driving distance to every other node was calculated in a preprocessing step. This precalculated data was then used for the calculation of transportation costs during the simulation.

- In the previous paper, trust between contract partners was modeled by assigning a random trust value at the beginning of the simulation to each buyer-seller-pair (therein called "friendship-value"). This trust value remained constant throughout the whole simulation. Now, the trust between contract partners changes depending on the success of negotiations and deliveries. If an agent A contacts another agent B for the first time, the initial trust value of agent A to agent B is the average of the trust values of all other agents to agent B, which can be interpreted as its reputation.
- The interaction protocol, i.e. how new contracts are negotiated, was adapted based on the knowledge gathered in interviews and workshops with different stakeholders. The most important difference to the previous interaction protocol is that offers are now evaluated one after the other, and not by comparing multiple offers and selecting the best ones like in the previous paper. This leads to different requirements concerning the decision behavior of the agents. While in the previous paper, AHP (Analytic Hierarchy Process, cf. Saaty, 2008) was used, this approach was not usable anymore as AHP requires multiple alternatives that can be compared. Now, an algorithm was needed to evaluate an offer on its own. Therefore, each agent was equipped with a utility function that can be used to evaluate potential contracts. These utility functions are based on discrete choice experiments (DCEs), a preference elicitation method based on random utility theory.

The last item, using DCEs to elicit the preferences of market participants, is the main topic of this paper. This approach is demonstrated with DCEs conducted with public forest managers in the cantons of Grisons and Aargau. The setup of the DCE is explained and different DCE evaluation methods are compared. It is shown how the results from the DCEs are used to equip each public forest manager agent with an individual, empirically-based utility function. The utility function includes an error component, which reflects non-measurable factors in the decision of a market participant. The error component is a central element in random utility theory. The role of it in the utility functions of the agents is explained and analyzed in the paper.

The paper concludes that using DCEs to parameterize the decision behavior of the agents is a suitable method to enhance the empirical foundation of an ABM. Especially using the Hierarchical Bayes (HB) approach to evaluate a DCE is beneficial, as HB calculates individual utilities for each participant in the DCE, so that it is possible to assign individual, empirically founded utilities to each agent in the model.

Chapter 3 presents the paper as it is published in the journal *JASSS (Journal of Artificial Societies and Social Simulation)*.

1.3.3 Empirical validation of an agent-based model of wood markets in Switzerland

Holm, S., Hilty, L.M., Lemm, R., & Thees, O. (2018). Empirical validation of an agent-based model of wood markets in Switzerland. *PLoS ONE*, 13(1):e0190605. doi:10.1371/journal.pone.0190605

This paper demonstrates and evaluates the efforts of validating the model. The empirical validation of the model is an important step towards its use for policy analysis. Some improvements of the model were necessary prior to validation, in order to prepare it for a later simulation of the defined scenarios. Compared to the model in the previous paper, the most important changes are the following:

- The three markets which were already present in the previous paper (for sawlogs, energy wood, and industrial wood) are now further divided into a market for softwood and one for hardwood. Distinguishing softwood and hardwood is important both on the supply and demand side. On the former because the percentages of available softwood and hardwood in the forests depends on the modeled region. On the latter because the different properties of softwood and hardwood result in different demand for them, depending on how the wood is intended to be used.
- There are now nine agent types modeled: two supplier types (public forest managers and private forest owners), two types of intermediaries (bundling organizations and traders), one demander type in each of the three markets (sawmills, energy wood buyers, and industrial wood buyers), and importer and exporter agents (cf. Figure 4.1 in chapter 4).
- The model boundary problem identified in the first paper has been addressed, details are presented in section 4.2.1.2.

After an overview of various calibration and validation approaches, it is shown in detail how the model was calibrated and validated. This was done by using statistical data from the Swiss Federal Statistical Office, data from own surveys, and with a case study. The paper concludes that the outcome of the validation qualifies the model to be used for policy analysis regarding the defined scenarios. Chapter 4 presents the paper as it is published in the journal *PLOS ONE*.

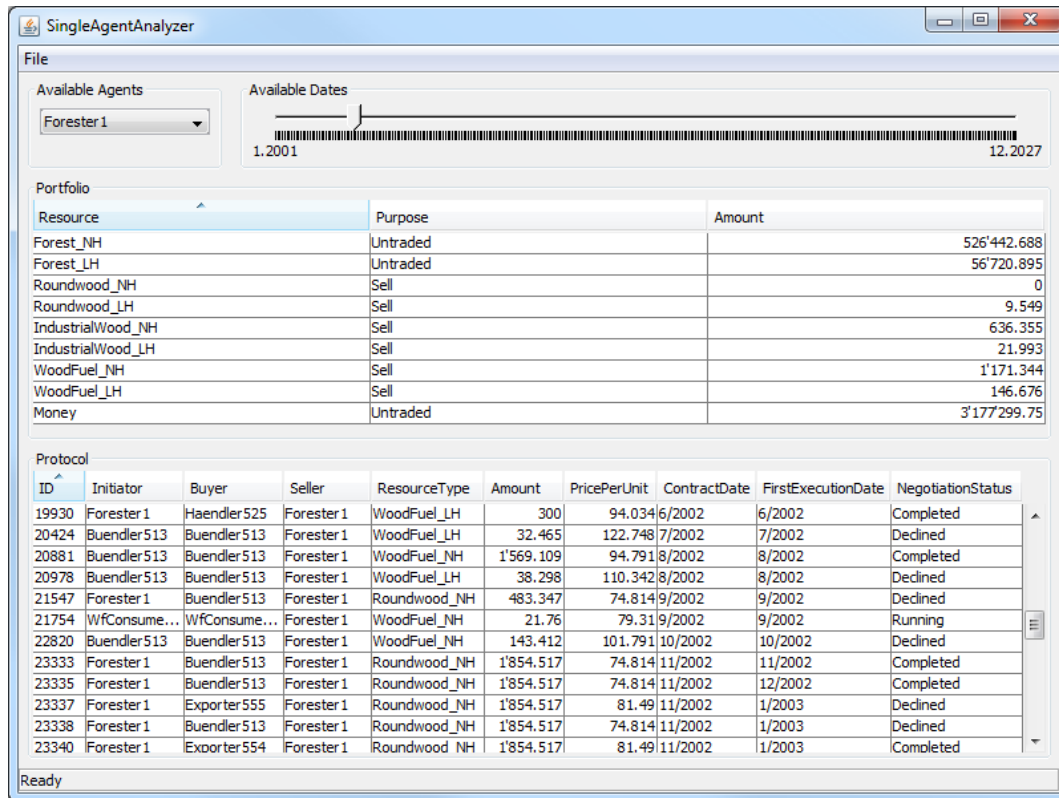


Figure 1.3: **SingleAgentAnalyzer**. This tool, developed by the author of this thesis, allows to trace individual agents in more detail in a post-processing step. For each simulated time step, the amount in stock of the different wood assortments and the status of ongoing negotiations of an agent can be examined. This tool is very helpful in the earlier stages of model development to verify and validate the model, in later stages to analyze the output of simulated scenarios, as it can help to track how aggregated behavior emerges from individual decisions. The tool is also shortly described in section 4.2.2.2 (bullet point "Traces") of the paper presented in chapter 4.

1.3.4 An Agent-Based Model of Wood Markets: Scenario Analysis

Holm, S., Thees, O., Lemm, R., Olschewski, R., & Hilty, L.M. (2018). An Agent-Based Model of Wood Markets: Scenario Analysis. Submitted to *Forest Policy and Economics*⁴.

In this paper, several politically relevant scenarios were simulated and analyzed. Some of the scenarios defined in the proposal of this thesis have been exchanged, as during the course of this thesis, additional scenarios gained political relevance. All simulations

⁴Shortly before this thesis was handed in, the editor of the journal rejected the paper but encouraged the authors to resubmit it after "some additional efforts of updating, revising, and editing".

start in the year 2001 and end in 2027, allowing a prediction⁵ for the years 2018-2027. The following scenarios were simulated:

- A business-as-usual scenario, working as a base-line for the comparison with the other scenarios
- A scenario where one of the two types of intermediaries, the bundling organizations, disappear in 2017
- A scenario where the influence of the profit-orientation of forest owners was analyzed
- Two scenarios where the influence of an increasing/decreasing exchange rate CHF-EUR was analyzed
- A scenario where the consequence of set-asides were analyzed

These scenarios differ from the five scenarios defined in section 1.2. The first scenario defined therein ("Domat/Ems case") was used for validation purposes in the paper summarized in the previous section. Two of the others ("Market Entry/Exit of bulk consumers" and "Having binding contracts instead of lose agreements") were exchanged because further scenarios became more relevant during the course of this thesis (however, the model is capable to simulate these originally defined scenarios). One was discarded ("Motivation of inactive suppliers") because it was recognized that the problem behind this scenario, i.e. how to motivate private forest owners to sell wood, is not something that can be simulated by this model, but rather a matter of attitude of private forest owners that should be investigated differently.

The paper evaluates and discusses these scenarios concerning annually sold amounts by wood suppliers, prices paid by demanders, and sales volumes of the two types of intermediaries in the market (bundling organizations and traders). Chapter 5 presents the paper as it has been submitted to the journal *Forest Policy and Economics*.

1.4 Limitations

A question which has to be asked if a model should be used for policy analysis is, can we trust the model? The concerns related to this question are addressed firstly by the thorough validation described in chapter 4, secondly by discussing the necessary steps for a careful interpretation of simulation results in section 5.4.

The model is currently parameterized and validated only for a single region (the canton of Grisons). This implies two risks: the risk that the model can not be parameterized for another region, and the risk of over-parameterization (overfitting) concerning the current region and time period used for validation. The first risk is considered low. The evaluation of the various surveys and experiments conducted in different regions indicated where the model needs to be parameterizable. This knowledge was taken into

⁵The term prediction is here used, as in the paper itself, according to the definition of Heath et al. (2009). This means that the model is used for "if-then" analyses, where unknown exogenous factors are assumed (the "if") and the consequences of having these factors set to certain values are analyzed (the "then").

account during the model building process, so that the model allows parameterization for other regions. The second risk is more difficult to assess. A parameterization of the model for further regions and the validation with further time series, can reduce the risk of having an over-parameterized model and confirm the applicability of the model to other regions. As empirical data for other regions has already been collected, the parameterization for further regions is planned and considered an important next step to improve the model's credibility for its use for policy analysis.

1.5 Future Work

The directions of future research can be categorized as follows:

- **Model application:** The model will be used for policy analysis. A first concrete project with a Swiss canton, in which a planned policy measure should be analyzed prior to its implementation, is in preparation. Model application is the most crucial point of this list, as it is the main legitimation for conducting further research related to this model (cf. guideline 2 of the design science research (DSR) approach).
- **Model parameterization:** An important requirement of the model, as stated in guideline 1 of the DSR approach, is its ability to simulate the wood markets of different regions in Switzerland. The model has been prepared to allow the parameterization for different regions. At the moment, the model is parameterized with data from the canton of Grisons. Empirical data required to parameterize the model for other regions has already been gathered for the cantons of Aargau and Bern. Parameterizing the model with this data will enable it to be used for policy analysis for further regions.
- **Model validation:** Parameterizing the model with data from further regions requires additional validation efforts, with validation data for these regions. Additionally, as soon as up-to-date time series from the Federal Statistical Office are available, these can be used to test whether or how accurately the model was able to predict the development of prices and traded quantities. On the one hand, this process can show where the model should be adapted to further increase its validity. On the other hand, such test data can also be used to reduce the risk of having an over-parameterized model, e.g. by trying not to introduce new parameters to fit the new data, or even better, reducing the set of used parameters.
- **Model analysis:** As the model is stochastic, the simulation results presented in the chapters 2-5 usually represent the average of 100 simulation runs with different random seeds. A deeper analysis of the variability of the development of observed variables across different random seeds could provide additional insights for policy analysis. This is especially motivated by observed phenomena such as the one shown in Figure 1.4.
- **Model presentation:** Currently, a map showing trading relations can be observed in real-time during the simulation, but the majority of model output is

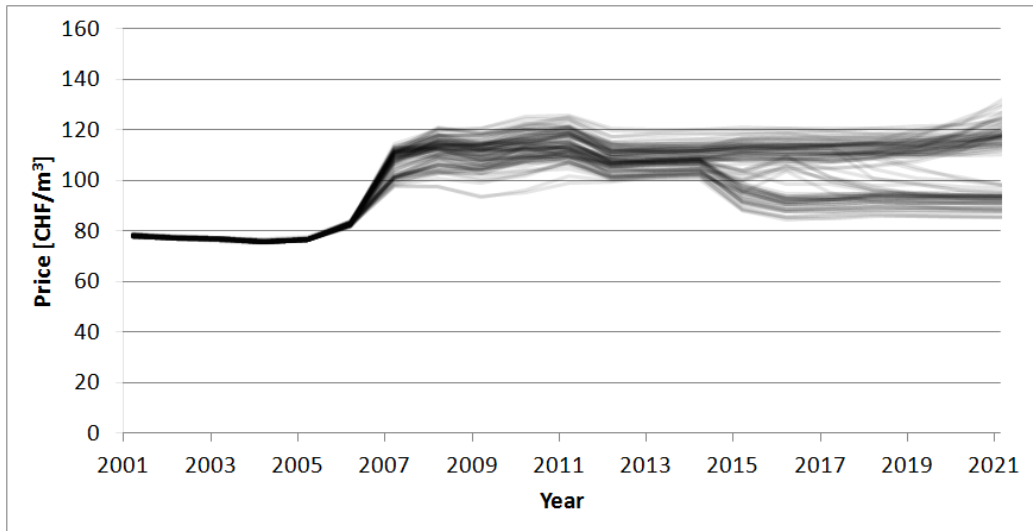


Figure 1.4: **Distribution of a variable across different random seeds.** The figure shows the development of average prices paid for sawlogs over time. Each line represents the development of this variable in a simulation run initialized with a different random seed. It can be observed that around 2015 the development of the variable diverges into two distinct directions. At a closer look it even seems that the divergence starts already around 2010. The reason for such a phenomenon is not yet clarified, but indicates the presence of a threshold at a certain point in time with a strong impact on the future development of the observed variable. The investigation of such thresholds could be interesting for policy analysis, if the possibility that this is an artifact can be excluded.

written to files that need to be analyzed in a post-processing step. Observing simulations in real-time is especially interesting for presentations, as it can give the audience a better understanding of the model. In a parallel project, a prototype of a tool enabling a better presentation of (real-time) simulation results was developed (Lotzmann, 2017a). It also offers the possibility to modify a reduced set of model parameters spontaneously (within the GUI) to simulate and compare simple scenarios. Further development of this tool could facilitate a more comprehensible communication of the model and simulation results to stakeholders.

- **Model usability:** Until now, the model is mainly developed, adapted and run by a single person, which is the author of this thesis. Usability should be increased to enable a larger group of people to use the model for research purposes, even without needing programming skills. A prototype of a tool which simplifies using the model has already been developed in a parallel project (Lotzmann, 2017b).
- **Model simplification:** Edmonds and Moss (2004) differentiate between two diametrically opposed modeling approaches, the KISS-principle ("keep it simple, stupid!") and the KIDS-principle ("keep it descriptive, stupid!"). The model here was built according to the KIDS-principle: as much as possible of the available knowledge about these markets was incorporated into the model, thereby

avoiding an a-priori over-simplification of the model (cf. section 4.4). This means, however, that there may be parts of the model which can be simplified or even removed without losing model accuracy. Identifying such parts and simplifying them could improve the comprehensibility, communicability, and error-proneness of the model.

- **Model refinement:** A crucial design element in an ABM is the way how agents interact. The interaction protocol for this ABM, which is the same for all agents in the model, is based on the knowledge gained in many workshops and interviews with stakeholders. It was designed with the goal to adequately represent the conclusion of business transactions in the markets under study. It has two stages (Figure 1.5), though only the first one has been described in the publications of this thesis so far. The second stage offers the possibility to simulate events such as not delivering the agreed quantity or insufficient payment. Currently, this second stage is simulated, but all agents always attend to their duties. Research on the influence of this behavior could provide additional insights. Moreover, it would allow the simulation of further scenarios, such as the influence of a bad payment moral, the impossibility to deliver wood on time because of bad weather conditions, or opportunistic behavior, e.g. not fulfilling a contract if there is a possibility to deliver to another customer who pays more.
- **Model expansion:** A long-term goal already declared in the PhD proposal is to expand the model so that it represents not only single regions of Switzerland, but the whole country (cf. guideline 1 of the DSR approach). This will require that some model parameters can be set per region to account for regional peculiarities e.g. in the decision behavior of the agents, or in the shares of hardwood and softwood in the forests.

1.5. FUTURE WORK

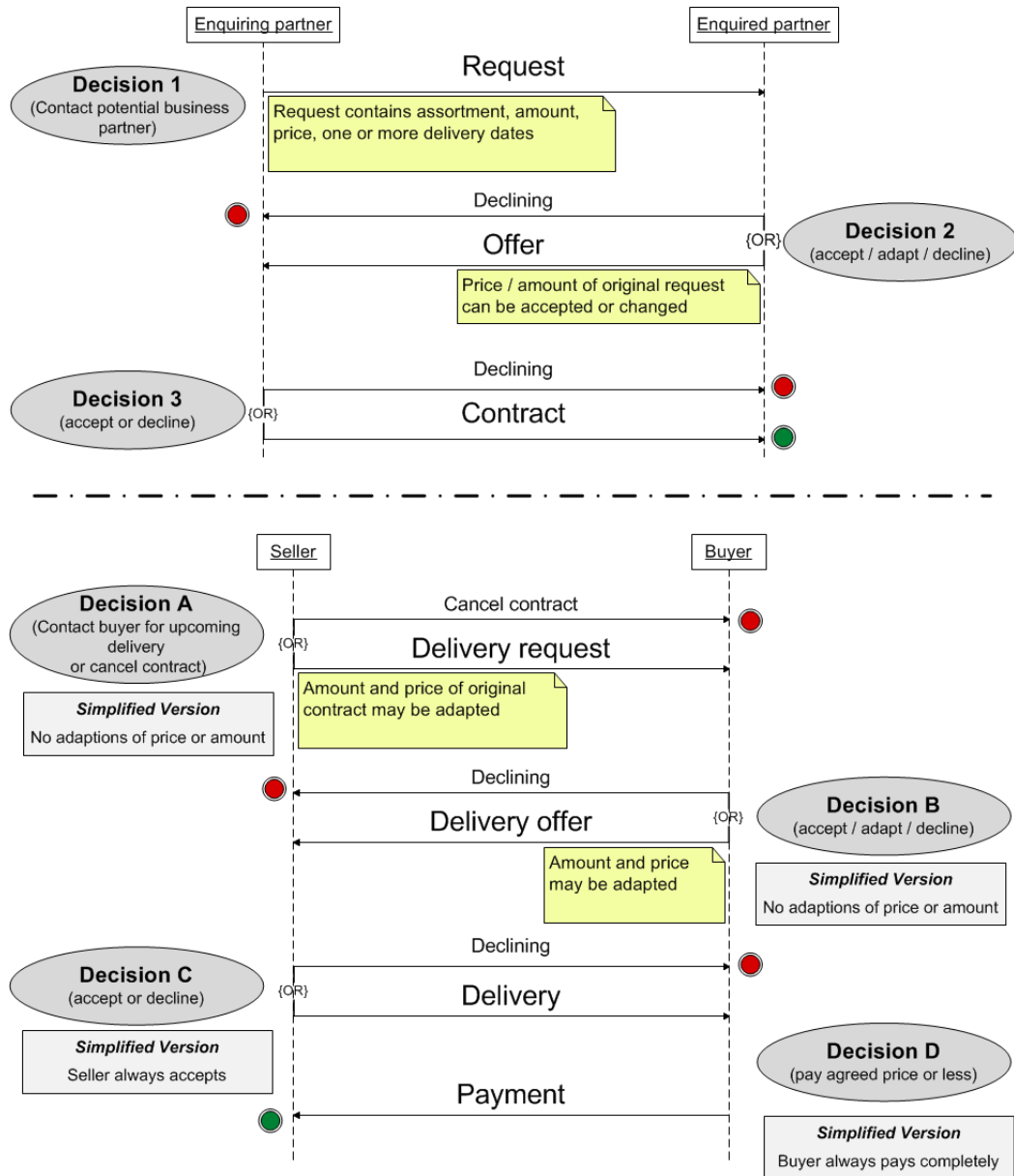


Figure 1.5: **Interaction protocol of the agents.** The interaction protocol has two stages. In the first stage (upper part), a contract is concluded and one or more delivery dates are agreed upon. Prior to every agreed delivery date, the second stage of the protocol (lower part) is executed. The seller thereby contacts the buyer in order to discuss the necessity of changes concerning amount or price. If they manage to agree, the seller delivers and the buyer pays, though the payment can be smaller than agreed. In a simplified version of the protocol used in the publications comprised by this thesis, all agents are always compliant in the second stage.

1.6 Conclusions

This thesis comprises four journal papers each showing a different stage of the development of an agent-based model of wood markets in Switzerland. A first version of the model showed where further research had to be conducted (publication in chapter 2). The concept of using discrete choice experiments to parameterize agent-based models with empirical decision behavior data was elaborated afterwards (publication in chapter 3). Various surveys and experiments were conducted in a next step. Parts of the obtained data were used to parameterize the model, other parts to validate the model (publication in chapter 4). Finally, several politically relevant scenarios were simulated, their output was analyzed, and the implications of these results were presented (publication in chapter 5).

The research of this thesis was motivated by the problem that the sustainable potential of the resource wood is not used in Switzerland, and the processes in the wood markets and the behavior of the market participants are difficult to understand. Yet a better understanding is the prerequisite to plan policy measures and evaluate their potential consequences.

The model developed in this thesis improves the understanding of the markets under study. It offers the possibility to conduct experiments *in silico* to analyze how the structure of these markets influences the availability of wood. Policy measures can be simulated prior to their implementation and analyzed concerning their potential consequences, making the use of this model interesting for policy makers.

The model as final artifact of this thesis is not the only outcome of this thesis. The design process lead to solutions for problems relevant also to other market modelers, for example how empirical data of the market participants' decision behavior can be incorporated into an agent-based model by using discrete choice experiments, or the presented approach of handling the model boundary problem. And – as already concluded in the validation paper (section 4.4) – having a validated model to be used for policy analysis is not the only reward, the journey is also a considerable part of it: The knowledge needed to build such a model needs to be gathered first, and this process already leads to many valuable insights about the markets under study.

1.A Appendix A: The seven guidelines of DSR: a comparison of the proposal with the actual outcome of the thesis

The following paragraphs name the seven guidelines for conducting effective design-science research (DSR) according to Hevner et al. (2004). Additionally, a comparison between how it was stated in the research proposal (Holm, 2014) to address each of these guidelines, and how they were actually addressed in this thesis is given.

Guideline 1: Design as an Artifact. *Design research must produce a viable artifact in the form of a construct, a method, or an instantiation.*

Proposal: "The output of this PhD thesis is a simulation program that is able to simulate the Swiss wood market. The artifact is instantiated with the relevant real-world data for the Canton of Graubünden and Canton of Aargau in order to simulate the defined wood market scenarios. By using empirical data from two substantially different Cantons, we will construct a generic model that can be specialized with the peculiarities of a Canton. With this approach, it should finally be possible to construct an ABM of the entire Swiss wood market, applying different regional peculiarities to agents at a specific location."

Thesis: An agent-based model of the wood markets in Switzerland has been developed, instantiable with data of different regions. Currently, it is instantiated with empirical data from the canton of Grisons, and also extensively validated for this canton (section 4). Empirical data has been gathered from three cantons, Grisons, Aargau, and Bern in order to use their peculiarities to build a generic model of Swiss wood markets. Some surveys covered Switzerland as a whole (section 4). Several scenarios have been simulated and analyzed (section 5); some of the scenarios defined in the proposal were exchanged to scenarios that became politically more relevant in the course of the study. The possibility to expand the model to represent Switzerland as a whole is shortly discussed at the end of section 1.5.

Guideline 2: Problem relevance. *The objective of the design science research is to develop technology-based solutions to important and relevant business problems.*

Proposal: "The relevance is given by the report of Bundesrat (2011), the enclosing NFP-project, and the domain problem it is intended to solve. We want to improve our knowledge on how the availability of wood in Switzerland can be influenced. We do this by simulating different scenarios developed with forest political representatives of the study Cantons Aargau and Graubünden. Future use of the model as a tool to support political decision making is strived for."

Thesis: The knowledge about these markets has been improved in several ways. First, the process of building the model improved the knowledge on mechanisms influencing wood availability. Second, by gathering empirical data necessary to instantiate the model, knowledge about the behavior of the market participants and the market structure has been improved. Third, the simulation of scenarios improved the knowledge on

how the availability of wood in Switzerland can be influenced (section 5). The model is now ready to be used as a tool to support political decision making.

Guideline 3: Design evaluation. *The utility, quality, and efficacy of a design artifact must be rigorously demonstrated via well-executed evaluation methods.*

Proposal: "The evaluation is ensured by the following methods. First, we conduct discrete choice experiments (DCEs) with the agents real-world counterparts to create a decision model that is based on random utility theory. Second, we continuously review the model output with domain experts. Third, we try to reproduce existing scenarios such as the Domat/Ems case with our model to validate it."

Thesis: Discrete choice experiments were conducted with several market participant groups (sections 3 and 4). The model was rigorously validated with statistical data available from the Swiss Federal Statistical Office, the data gathered in own surveys, and by discussing the model output with domain experts. The validation also included the reproduction of the historical event of the sawmill in Domat/Ems (section 4.2.3.3).

Guideline 4: Research contributions. *Effective design science research must provide clear and verifiable contributions in the areas of the design artifact, design foundations, and/or design methodologies.*

Proposal: "The research contribution is twofold. First, we show how discrete choice experiments can be used to improve the decision procedure of the agents in an agent-based model. We especially focus on the compatibility with the random utility theory and the use of its error component in combination with the stochasticity in agent-based models. Second, we explore the potential of agent-based modeling to explain the Swiss wood market."

Thesis: The method of combining agent-based modeling and discrete choice experiments and the usefulness of this approach was demonstrated in the paper shown in section 3. Several findings relevant to other market modelers, such as our approach to solve the boundary problem, were described (section 4). The potential of using an ABM to analyze the Swiss wood market could be approved (sections 4 and 5).

Guideline 5: Research rigor. *Design science research relies upon the application of rigorous methods in both the construction and evaluation of the design artifact.*

Proposal: "For the construction of the conceptual model, besides classical interviews with domain experts and market actors, we conduct discrete choice experiments that are based on the random utility theory. The computer model will be implemented in Java, in order to have a high level of flexibility. To describe and communicate the model, we will use the ODD-protocol (Grimm et al., 2006)."

Thesis: As mentioned before, DCEs were conducted (section 3). An intense validation of the model was conducted, using multiple validation approaches (section 4). The computer model was implemented in Java. State-of-the-art software engineering principles were applied to facilitate future maintainability and flexibility in expanding the

model. The ODD-protocol was used to describe the first versions of the model. However, as the model became larger, the updating of the ODD-protocol was discontinued. The central idea behind the ODD-protocol is enabling replication of existing models (Grimm et al., 2006). With the increasing complexity of the model, it was not possible to manage a document simultaneously to developing the code, detailed enough to enable exact replication. This is, in the opinion of the author, only possible by seeing the code. The code of the model is published together with this thesis. Nevertheless, the structure of the ODD-protocol guided the description of the model in the published research articles, where the most important parts of the ODD-protocol were described in a granularity and level of detail necessary for the comprehension of the article.

Guideline 6: Design as a search process. *The search for an effective artifact requires utilizing available means to reach desired ends while satisfying laws in the problem environment.*

Proposal: "We will have multiple iterations of implementing and improving the artifact. A first step (containing multiple iterations itself) was done in the foregoing work of Holm (2011) and Kostadinov et al. (2014). In the current work, we continuously compare our model and simulation results with the findings of the parallel projects (cf. Figure 1.6) and validate them with domain experts. In this iterative process, not only the validity of the model should be improved, but also the performance of the simulation program should be optimized, in order to simulate a sufficiently high number of agents. The final iteration is reached when (i) the five types of scenarios corresponding to the domain problem questions have been simulated and have led to feasible results, (ii) the usefulness of using agent-based modeling to simulate the Swiss wood fuel market is demonstrated, and (iii) the usefulness of using discrete choice experiments to improve the model validity is evaluated."

Note: The start of this thesis was in 2012, and the final version of the proposal was submitted shortly after the publication of Kostadinov et al. (2014)(chapter 2), and therefore Kostadinov et al. (2014) was already cited in the proposal.

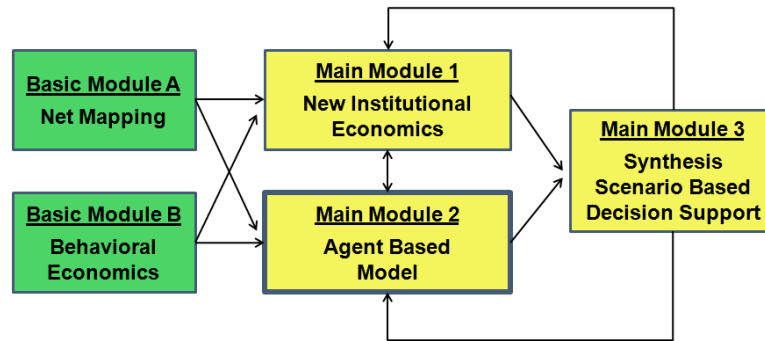


Figure 1.6: Module structure and cooperation between modules of the NRP66-project "Analyzing Swiss Wood Markets – An Institutional and Computational Economic Approach".

Thesis: Knowledge gained in the parallel projects was helpful in the model building process to complement the empirical data gathered in this project. The model valida-

tion process is described in chapter 4. The performance of the model was significantly improved compared to the first version of the model, both in terms of speed and memory consumption, so that a typical model run now lasts about 1-2 minutes (compared to 2-3 hours of the first version of the model). Several scenarios were simulated and analyzed (chapter 5). As mentioned in section 1.3.4, some of the scenarios defined in the proposal were exchanged to scenarios that became politically more relevant in the course of the study. The potential of an ABM to explain the Swiss wood market could be approved (sections 4 and 5), likewise the usefulness of using DCEs to improve the empirical validity of a model (section 1.3.2).

Guideline 7: Communication of research. *Design science research must be presented effectively to both technology-oriented and management-oriented audiences.*

Proposal: "The applied computer science audience might be interested in (i) further findings on using discrete choice experiments as an empirical method to improve the accuracy of the agents' decision behavior, and (ii) efficiently implementing an ABM with a large number of agents. The forestry science and economics audience is interested in findings that can improve the systematic understanding of wood market. Political decision-makers will be interested in measures to improve availability of wood in Switzerland."

Thesis: The research conducted in this thesis was published in several papers in peer-reviewed journals. After the first paper, which was already published by the time of writing the proposal, three additional papers were published (or submitted). Two of these are more targeted to the modeling and simulation community: the paper that examines the combination of ABMs and DCEs and the paper which describes the validation of the model and details about our approach to solve the model boundary problem. The last paper is more targeted at forestry policy makers as it demonstrates the application of the model. i.e. the simulation of several politically relevant scenarios.

Simulation of a Swiss wood fuel and roundwood market: An explorative study in agent-based modeling

Kostadinov, F., Holm, S., Steubing, B., Thees, O., & Lemm, R. (2014). Simulation of a Swiss wood fuel and roundwood market: An explorative study in agent-based modeling. *Forest Policy and Economics*, 38, 105-118.

Abstract

This study discusses the potential of applying agent-based modeling (ABM) to wood markets. A corresponding model of the wood market of a Swiss canton, consisting of a coupled roundwood and wood fuel market, is presented. The model includes wood-producing agents, such as public foresters and private forest owners, roundwood-consuming agents, such as sawmills, different classes of wood fuel consumers, and in-between wood traders. Other important model elements include agent interaction and negotiation, execution and scheduling structures, and agent adaptation mechanisms. Two sets of scenarios demonstrate the model's power for scenario exploration. The first set of scenarios analyzes the effects of an excess and scarce supply of wood on both markets. The second set looks for the optimal number of roundwood agents in the market from the perspective of the various stakeholders involved. Taking a more in-depth view of important design decisions and their pros and cons, this study argues that ABM offers new opportunities for the explorative study of wood markets as a result of these markets' special characteristics.

2.1 Introduction

The analysis of wood markets is a difficult endeavor for several reasons. First, wood markets tend to be imperfect markets. Uncertainties exist regarding the long-term development of forest wood supply due to varying climate change scenarios and the possible occurrence of calamities. Second, the theoretically available amount of wood is limited by natural tree growth and long-term ecological concerns, leading to the prescription of the *annual allowable cut (AAC)*. This measure can be relatively easily

estimated, yet the actually available amount of wood on a market depends strongly on other factors. For example, technological advances, especially in the harvesting industry, have increased productivity in recent decades, leading to long-term changes in production costs. Political agendas and legal restrictions also can enforce increased or decreased wood production, beyond what is economically justifiable. Societal values might demand accessibility to forests for functions other than wood production. Suppliers and demanders alike are adaptable; they learn from past and anticipate future developments. Finally, individual psychological and behavioral factors apply. In many European and North American countries, non-industrial, private forest owners often pursue personal goals other than market participation or profit maximization (Beach et al., 2005; Bohlin and Roos, 2002; Conway et al., 2003), to the extent that some of them never even offer their wood on the market. Third, wood market analysis is difficult because of the tight intertwining of the roundwood and wood fuel markets, which results in hard-to-predict cyclic dependencies between them.

Therefore, when modeling wood markets, it is desirable to have a modeling technique that can accommodate the complexity of the situation. Agent-based modeling (ABM) – and more specifically, agent-based computational economics – is a technique that allows developing market models using a bottom-up approach that includes individual market participants’ behavior. Whereas ABM shares some fundamental trade-offs with other modeling disciplines (i.e., model complexity versus traceability and understandability, degree of detail and richness of features versus desirable levels of aggregation and abstraction), it also offers some distinct promise. For example, ABM explicitly exposes the modeled relationship between the micro- and macro-levels of observed reality. It offers the possibility to observe emerging aggregate market behavior as a result of interactions of individualized agents. Therefore, it promises a means to investigate aggregated and averaged values, but it also can report individual data values at the micro-level. Similar to other simulation tools, ABM can tackle certain types of problems that are too hard to solve using classical analytical mathematical approaches (Maria, 1997). Simulation as a superclass of ABM also offers an alternative method to conduct otherwise infeasible experiments. One specific disadvantage of ABM is that it can aggravate the problem of limited computational power with regard to both processing speed and amassing data quantities.

Thus ABM has already been applied to a wide range of agricultural, land use, or ecological domains, though few authors have attempted to implement runnable agent-based models of wood markets. Troitzsch (2012) offers an introduction to the topic, and Gebetsroither et al. (2006) describe a compound ABM consisting of two interlinked but otherwise independent agent-based submodels. One submodel simulates tree growth in a forest, with the trees modeled as competing agents, and the other simulates a market of suppliers and demanders of timber. Outside the field of wood market simulation but still related to forestry, several agent-based models have been developed to simulate forestry management decisions (Pérez and Dragicevic, 2010; Purnomo and Guizol, 2006), explicate causal factors for deforestation in Mexico and the United States (Manson and Evans, 2007), and assess different demand-driven timber production strategies in Canada (Yáñez et al., 2009).

This study addresses the relative lack of applied knowledge in the field of agent-based wood market simulations by first expanding an agent-based model of a Swiss wood market and then exploring scenarios in which key supply and demand side parameters are varied. We followed the principles of the MAIA methodology (*modeling agent systems based on institutional analysis*; Ghorbani et al., 2011) to create an agent-based model for the Swiss canton Aargau. It is based on precedent model versions, one first implemented by Olschewski et al. (2009), which was still relying on standard microeconomic assumptions, and a subsequent, more detailed version introduced by Kostadinov et al. (2012). We explored the model’s capabilities by simulating two sets of economic scenarios and comparing them with a base scenario calibrated with default data from Aargau. In the first set of scenarios, we varied the supply side to simulate scarcity and excess supply situations. In the second set of scenarios, the demand side was varied through differing numbers of sawmills in the market. We used these sets of scenarios to conduct qualitative analyses of trading prices, traded amounts, and further measures.

In Section 2.2 we present the model and its constitutive elements (e.g., markets, agents, agent interactions), as well as its scheduling, execution, and negotiation processes. Section 2.3 demonstrates the model’s application using explorative scenario analysis, including a base scenario and two sets of scenarios. In Section 2.4 we provide a critical review of the model’s fundamental design issues, before we conclude in Section 2.5 with a short summary of ABM’s strengths when applied to a Swiss wood market, as well as some limitations and suggestions for further research.

2.2 Model

The high degree of complexity and size of the model prevent us from giving a complete overview; we focus instead on core model elements. A complete model description, following the ODD protocol (overview, design concepts, and details; Grimm et al., 2006, 2010) is available elsewhere.¹

2.2.1 Model region and data

We chose the Swiss canton Aargau as the model region for several reasons. First, the data for this canton are relatively available. Second, Aargau takes a representative position among Swiss midland cantons in terms of its geographical location and conditions for wood production. Aargau is important for wood fuel production in Switzerland. Third, the number of agents to be modeled seemed manageable computationally and yet still sufficient to provide a high number of agent interactions. The model also could be transferred to and calibrated with data from other regions, whether other Swiss cantons or regions in countries with similar market structures, such as Germany or Austria.

¹This ODD protocol document is available at <http://www.wsl.ch/fe/waldressourcen/produktionssysteme/publikationen>.

Aargau has a size of 1404 km² and a population of approximately 620,000 people. The forest area in Aargau is approximately 49,000 ha (i.e. about one-third of the canton's area is forested). Public and semi-public organizations, such as municipalities and corporations, own 78% of the forests, whereas 22% are under private property. In the past years, an average of 435,000 m³ wood was used yearly, including 60% as stem wood and 40% as wood fuel or industrial wood. For the model, we refer to stem wood as roundwood, and the term wood fuel also includes industrial wood (Kanton Aargau, 2010).

The simulation model focuses only on forest wood production and consumption, including wood fuel produced from industrial waste wood; it excludes other sources, such as post-consumer wood.

The following data sources were used for model calibration:

- The number, size, and location of wood fuel heating systems in Switzerland, as provided by Holzenergie Schweiz (Primas et al., 2011).
- The number of foresters and amount of forest managed, provided by the third Swiss National Forest Inventory (Brändli, 2010).
- Past oil price developments (US Energy Information Administration, 2011), to determine, among other factors, how attractive it is for new wood fuel consumers to install wood fuel heating systems and thus enter the market.
- Classification and typification of foresters, private forest owners, and certain wood fuel consumers, based on qualitative interviews conducted with market participants, scientific studies of non-industrial private forest owners (Beach et al., 2005; Schaffner, 2008), and the authors' own expert knowledge.

2.2.2 Model elements

The model consists of markets in which agents, representing real-world market participants, sell and buy wood. Agents are grouped into classes, according to their market roles. They also are assigned a certain type, which represents the market participant's behavioral or decision characteristics.

2.2.2.1 Markets

Forests are modeled rudimentary as homogeneous, renewable resources of a certain size, with a natural upper growth limit equal to the AAC. Tree growth is equally distributed over time. The model does not include seasonal influences, changing weather conditions, calamities, or natural preconditions for forestry. We model both the roundwood and the wood fuel market. On the roundwood market, only roundwood is traded, whereas on the wood fuel market, only wood fuel is traded. Both are assumed to be homogeneous goods. We omit differences in tree species, product segments, and product qualities. Fig. 2.1 provides an overview of these markets and their agents.

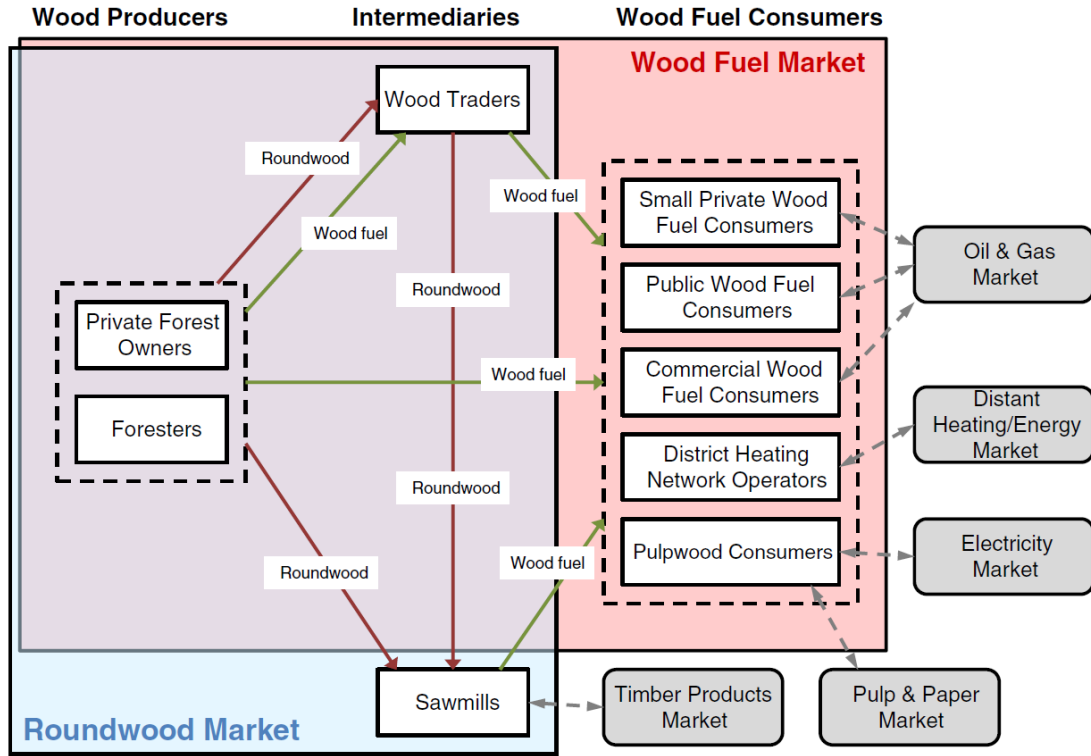


Figure 2.1: Overview of modeled roundwood and wood fuel markets, agent classes (white boxes), and exogenous markets (gray boxes). Brown arrows indicate flows of roundwood, and green ones denote flows of wood fuel. Sellers of either roundwood or wood fuel are at the arrow's tail, and buyers are at its head. Dashed, gray arrows indicate agents' relationships with exogenous markets.

We model five markets purely exogenously: the timber products market, the pulp and paper market, the district heating market, the electricity market, and the oil and gas market. Although some agents depend on these highly aggregated markets in one way or another, no real agent interaction occurs, as is the case for the roundwood and wood fuel markets. In other words, these markets constitute the system's boundaries.

2.2.2.2 Agents and agent classes

Table 2.1 provides an overview of the agent classes. The presented agent characteristics are based on the data sources cited in the section "Model region and data". All agents have a fixed geographical location and a portfolio containing the agent's resources, which consist of forest (wood producers only), a stock of roundwood and/or wood fuel (wood consumers only), money (all agents), and possibly contracts. Agents act as suppliers, demanders, or intermediaries of roundwood and wood fuel. Not all agent classes are active in both markets. The columns "roundwood market" and "wood fuel market" in Table 2.1 show the roles of agents in a market.

Agents also maintain a "phone book" of other agents located nearby, which they use to find suitable trading partners during the negotiation process. The larger an agent is, the more entries the phone book contains.

The column "Initial # of agents" in Table 2.1 lists the initial numbers of simulated agents. These numbers can vary significantly throughout the simulation, depending on market entry and exit of agents. Because of limited computational power, it was necessary to aggregate multiple real-world market participants per class into fewer scaled-down agents. However, it was not possible to use the same scaling factor for all agent classes. Whereas certain agent classes correspond to several thousand real-world market participants, for other classes only one or two market participants exist. The corresponding scaling factors also appear in the table. For example, 43 commercial wood fuel-consuming agents with a scaling factor of 10 represent 430 real-world market participants. The effect of scaling on the simulation results is not clear. Several studies show how to technically parallelize the computation of agent-based models (Da-Jun et al., 2004; Lysenko and D'Souza, 2008), but no studies directly address the effects of scaling.

The column "production or consumption capacity" provides an overview of the market impact of an agent class in a base scenario. For example, foresters on average manage 80% of all forest available in the model, but private forest owners manage only 20%. How much roundwood and wood fuel they effectively produce cannot be directly deduced from the table, but it is an emergent result in the simulation. Roughly half the private forest owners² remain mostly inactive in a base scenario and do not produce roundwood or wood fuel at all. They only actively harvest and produce when wood prices cross an individually set threshold value. This threshold is set at 20%³ above the initialized wood prices.

²Estimation, recommended by domain experts.

³Assumption, not based on empirical data.

Agent class	Description	Round-wood market	Wood fuel market	Initial # of agents	Scaling factor	Production or consumption capacity	Default agent types
<i>Forester</i>	Usually full-time professionals managing forests on behalf of third-party owners (mainly municipalities).	Supplier	Supplier	73	1	Manage 80% of forest	50% profit, 50% friendship
<i>Private forest owner</i>	Own forests themselves. Average owned/managed patches are usually much smaller than the ones managed by foresters. In a base scenario, 50% of private forest owners have little interest in wood production and remain mostly inactive throughout the simulation.	Supplier	Supplier	285	50	Manage 20% of forest	50% profit, 50% friendship
<i>Wood trader</i>	Solely act as intermediaries, buying and selling roundwood and wood fuel on both markets. Do not produce or consume roundwood or wood fuel themselves.	Intermediary	Intermediary	43	1	Do not manage forest, do not consume wood	100% standard
<i>Sawmill</i>	Only class of roundwood consumers in the model, but they also act as suppliers of wood fuel on wood fuel market.	Consumer	Supplier	21	1	100% of RW consumption (16,300 m ³ p.m.)	100% standard
<i>Small private wood fuel consumer</i>	Single detached houses with a wood fuel heating system consuming small amounts of wood fuel.	–	Consumer	107	10	5% of WF consumption (1800 m ³ p.m.)	100% standard
<i>Commercial wood fuel consumer</i>	Private corporate entities running larger (corporate) buildings, up to small compounds with a wood fuel heating system installed.	–	Consumer	43	10	30% of WF consumption (11,700 m ³ p.m.)	100% standard
<i>Public wood fuel consumer</i>	Mostly municipalities or similar organizations running publicly owned buildings such as schools and fire departments. They enjoy preferential treatment by foresters.	–	Consumer	32	10	22% of WF consumption (8800 m ³ p.m.)	100% standard
<i>District heating network operator</i>	Commercial energy/heat producers. The produced heat is sold to houses attached to the same heating network.	–	Consumer	21	1	9% of WF consumption (3400 m ³ p.m.)	100% standard
<i>Pulpwood consumer</i>	Chemical and paper industry. They compete with other wood fuel consumers for the same good.	–	Consumer	2	1	34% of WF consumption (13,300 m ³ p.m.)	100% standard

Table 2.1: Modeled agent classes and their characteristics. Numbers on wood consumption are given in m³ per month (= m³ p.m.; RW = roundwood, WF = wood fuel).

Sawmills are the only roundwood consumers in the simulation. Wood fuel production is a side effect of their roundwood processing activity. Thus, they also act as wood fuel sellers in the wood fuel market. Wood traders do not produce or consume wood themselves; they only trade it. They can buy wood from foresters and private forest owners at a reduced price ($-5 \text{ CHF/m}^3 \text{ wood}$)⁴ because, according to the model design, they harvest the trees themselves. Pulpwood consumers are the largest wood fuel-consuming agents; combined, they consume roughly 34% of total wood fuel at the beginning of the simulation. Only two of them appear in the model. Small private wood fuel consumers represent the largest number of wood fuel consumers, but taken together, they only consume 5% of all wood fuel at the beginning of the simulation. The other classes of wood fuel consumers are somewhere in between.

Public wood fuel consumers enjoy preferential treatment by foresters. Foresters that receive multiple requests for wood fuel by several public and non-public wood fuel consumers always accept the public ones first, as long as they meet a minimal standard, even if the requests are otherwise inferior to those of non-public wood fuel consumers.

2.2.2.3 Demand behavior

Agents that demand wood are also producers. They produce either heat and "energy" or pulp and paper, in the case of wood fuel consumers, and timber products, in the case of roundwood consumers. Their goal is to keep their output per time unit constant. Every consumer agent has an individually set, unchanging, monthly need for wood. In each period, the agent uses up an amount of roundwood or wood fuel according to its need and then reevaluates its wood stock and tries to buy as much wood on the market as is required to refill its stock for the next period. If for any reason an agent does not succeed in buying the demanded quantity of wood during one period, its demand for wood in the next period will rise accordingly. If its attempts remain unsuccessful for more than a month, the agent will increase its willingness-to-pay price by 1%. If instead the agent can completely satisfy its demand for a month, its willingness-to-pay price decreases by 1% at the end of the month. Collectively, this leads to rising prices in a scarcity and falling prices in an excess supply situation. The 1% adaptation value is set at the start of the simulation and remains the same for all consumer agents, though it theoretically could be set per agent class, agent type, or individual agent. The higher it is, the faster price adaptations occur. This adaptation value is currently not empirically grounded; it represents a design decision. Should an agent fail to cover its need for a prolonged time or, in the case of sawmills or pulpwood consumers, run out of money, it will leave the market. The long-term, aggregated market demand therefore can decrease from market exit of consumer agents and increase from their market entry. If wood fuel prices are lower than oil prices, more new wood fuel consumers make a decision to install a wood fuel heating system and enter the market. In the short run, wood fuel demand is constant, because wood fuel is not substitutable. Roundwood consumers take into account combined criteria based on whether to enter the market or not. First, they consider the roundwood price development over the past two years. If it is falling, they tend to enter the market. Second, they consider the AAC utilization

⁴Estimation, recommended by domain experts

rate (see Section 2.3). The lower it is, the higher is the probability that new sawmills will enter the market.

2.2.2.4 Supply behavior

Production of roundwood, and therefore the roundwood supply in the short run, is mainly a demand-driven process. Wood producers may, but are not forced to, produce roundwood according to the demand they face. If they do not exploit the AAC at a given point in time, the corresponding wood quantity will still be at their disposal in later periods.

Production of wood fuel and therefore the wood fuel supply in the short run depends on roundwood production. A certain low quantity of wood fuel is produced constantly during maintenance work in the forests, and because wood producers try to cover fixed costs (e.g., employees' salaries) by maintaining a minimal constant workforce utilization. Yet the majority of wood fuel is produced either during roundwood production by wood producers or during the timber product manufacturing process by sawmills.

Wood producers observe the attractiveness of the roundwood market in relation to the wood fuel market. This attractiveness is measured as the relationship between the roundwood price and the wood fuel price. If this relationship is in favor of wood fuel, it is worth producing more wood fuel from wood segments otherwise still suitable as roundwood, and vice versa. The corresponding output ratio is called the wood fuel portion of the total tree mass (= WFM):

$$\text{WFM} = \frac{\text{Wood fuel mass of harvested tree}}{\text{Total mass of harvested tree}} \quad (2.1)$$

with bounds set to $0.2 \leq \text{WFM} \leq 0.6$. Wood producers can never produce less than 20% of wood fuel per harvested tree, or more than 60%. As a consequence, consumers of both roundwood and wood fuel markets compete to a certain degree for the same good. Significant changes in one market's dynamics might influence the other market as well.

Wood producers can adapt to long-term changes of demand only to a limited extent. Within certain boundaries, they can decide to produce more roundwood at the cost of wood fuel, or vice versa, but they cannot significantly increase their output beyond the set AAC. This is because in the canton Aargau, as well as in Switzerland, upper limits to wood production are set by restrictions of space and territory and, thus, through set forest sizes, as well as for legal reasons that prescribe non-industrial forest management styles.

The aggregated long- and short-term market supplies for roundwood and wood fuel thus are emergent, discontinuous, interdependent functions with an upper limit. They are heavily dependent on the demand faced and other factors. Both supply and demand have a geographical dimension; suppliers and demanders tend to interact with the agents in their surroundings.

2.2.2.5 Decision-making process

Agents in a class can be categorized into different types according to their personal preference (or utility value) structure. Schaffner (2008) discusses a typification of private forest owners for the case of Germany, Austria, and Switzerland; Majumdar et al. (2008) do so for some southern states in the United States; and Boon et al. (2004) focus on Denmark. When facing the same decisions, agents of the same class and type apply the same value judgments in an equivalent situation. Therefore, a deterministic decision-making algorithm is required. Several authors quantify the decision-making processes of wood market participants. In two independent meta-studies, Amacher et al. (2003) and Beach et al. (2005) provide overviews of multiple econometric measures and their influences on non-industrial, private forest owners' management decisions. They agree, for example, that non-industrial private forest owner demographic characteristics, such as level of education, age, and professional occupation, influence their management decisions. Both Conway et al. (2003) and Størdal et al. (2008) use regression-based models to quantify non-industrial private forest owner behavior.

The current study adopts a different approach. An analytical hierarchy process (AHP; Saaty, 2008) is widely used in (sometimes automatable) supplier selection problems (Bruno et al., 2009). Similar to multi-criteria analysis, AHP is a standardized method for ranking different possible alternatives according to predefined, weighted selection criteria. One or multiple ranked alternatives then can be selected. Knoeri et al. (2011) apply AHP to operationalize agent behavior in an ABM. In our model, an agent's utility function and thus its decision-making process are also implemented as AHPs. Preferred deals get selected from a list of selling or buying opportunities. During the agent's AHP, a combination of three criteria is applied:

- *Profit criterion:* Sellers of roundwood and wood fuel want to maximize their monetary gains, whereas buyers want to minimize their expenditures. The profit criterion combines two measures equally: a price component and a quantity component. Low prices increase the price component value for buyers but decrease it for sellers. Furthermore, the ability to buy 100% of their needs through the same seller increases the quantity component value for buyers. For sellers, the quantity component value increases if they can sell all their wood at once to a single buyer.
- *Friendship value criterion:* Agents prefer selling to and buying from other agents with which they are friends. Friendship values are randomly assigned to pairs of suppliers and demanders during the simulation's start-up phase and remain unchanged throughout the simulation.
- *Geographical distance criterion:* This criterion represents two distinct but combinable utility values in the real world, namely, a preference to buy or sell from local forests, reflecting an inwardly felt connection with one's home place, and an agent's financially or ecologically based desires to minimize transport distances. Although in the model, agents do not pay transportation costs, they include the transportation distance as a criterion in their decision-making process.

Agents with the same AHP weights are assigned the same agent type. We use four default types for all agents in all classes: standard, profit-oriented, friendship-oriented, and distance-oriented types. Table 2.2 lists the weights used for each type.

Types	Weight profit criterion	Weight friendship criterion	Weight distance criterion
<i>Standard</i>	0.6	0.3	0.1
<i>Profit-oriented</i>	0.9	0.05	0.05
<i>Friendship-oriented</i>	0.05	0.9	0.05
<i>Distance-oriented</i>	0.05	0.05	0.9

Table 2.2: Weights assigned during AHP to different criteria by agent types.

The shares of each agent type per agent class in the base scenario appear in the column "Default agent types" in Table 2.1. Although we selected the criteria on the basis of qualitative interviews conducted with real-world market participants, the shares of each agent type listed in Table 2.1 and the weights applied to each criterion are not really empirically grounded.

Agents willing to pay high prices on the one hand and agents requesting larger quantities of wood on the other hand gain competitive advantages during the application of AHP. Because the friendship and distance criteria are statically set for the whole simulation, they can only distort competition, not intensify or weaken it.

2.2.3 Scheduling and execution

The main simulation process is split into sequentially executed subprocesses, as Fig. 2.2 shows. In MAIA terminology, they are *action situations*. Start and end are not real action situations; rather, they serve only to set up and tear down the simulation. The simulation is round based, and each round reflects a year's execution. Once a year, some agents can enter or leave the markets during the market entry and exit action situation. The roundwood market, the wood fuel market, and then the evaluation action situations are executed in sequence. This sequence gets repeated 12 times (= 12 months) per year. After a one-year cycle (one round) is completed, a new cycle starts.

Both market executions consist of two subsequent phases, repeated as pairs six times. In each phase, different agents act as sellers or buyers. Fig. 2.3 shows the implemented negotiation protocol and the involved agent classes for each phase in detail.

In each phase, buyers and sellers are activated in a random order. Both phases follow the same four main steps.

1. *Buyers make requests.* Buyers with demand for a certain good (roundwood or wood fuel) search for sellers in their phone books and send them a request with the demanded amount. They also add the price they are willing to pay to the request.

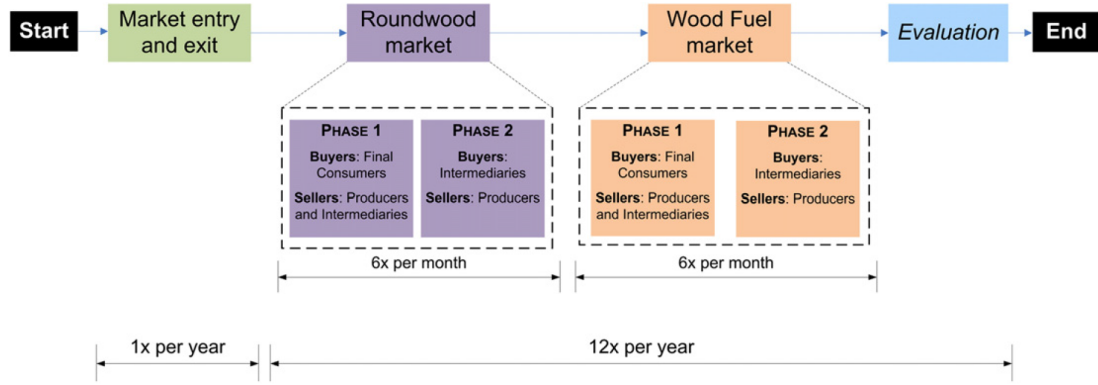


Figure 2.2: Overview of the main simulation process with action situations.

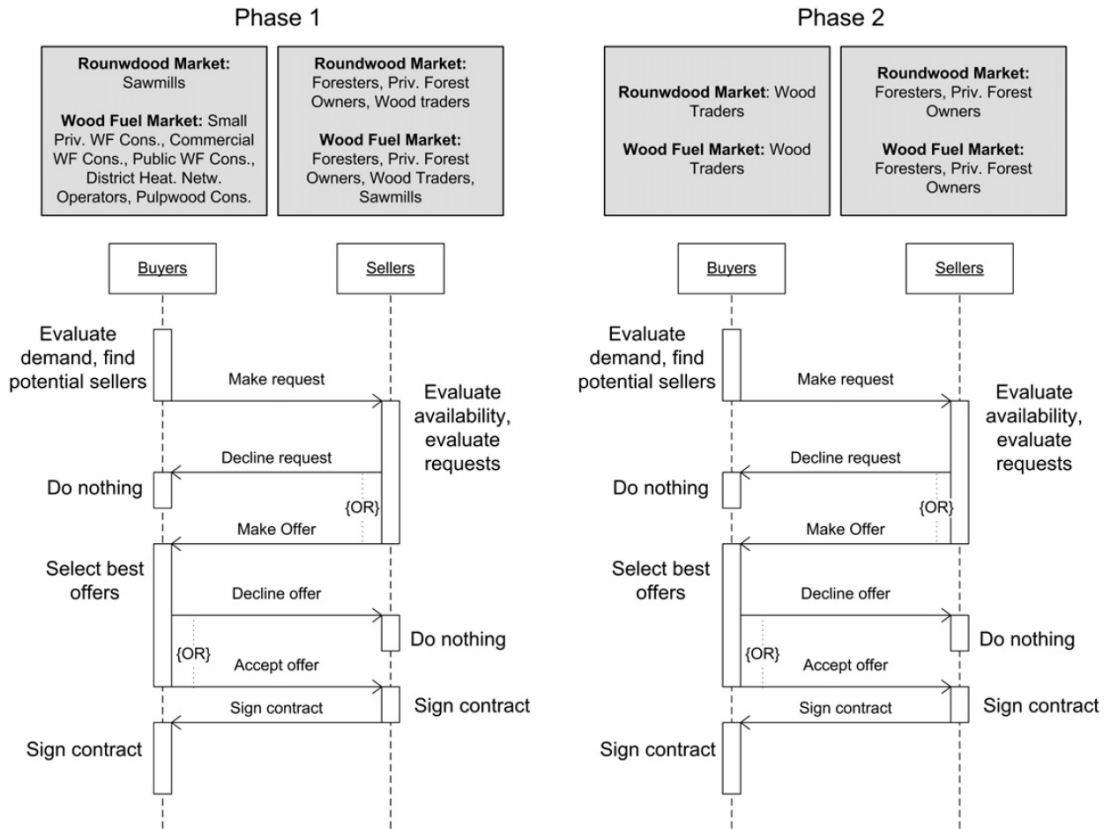


Figure 2.3: Interaction diagrams of the two-phase buyer/seller negotiation protocol for both roundwood and wood fuel markets.

2. *Sellers make offers.* Each seller agent checks if it has received any requests. If it has, it orders the requests with AHP, applying the already mentioned criteria so that it answers the most advantageous request first. Then it checks whether it has enough of the resource requested and whether the buyer's willingness-to-pay price lies above its own reservation price. If both conditions are met, the seller sends an offer to the buyer; otherwise, it declines the request.

3. *Signing contracts.* All buyer agents check whether they have received any offers for their requests. If so, they order the incoming offers with AHP, so that they answer the most advantageous first. If their demand has not been satisfied, they sign additional offers (i.e., accept the offer and are willing to pay the price set in the contract). When their demands are satisfied completely and unsigned offers still remain, they decline them all.
4. *Fulfilling contracts.* At the end of a round, all contracts marked as "signed" are fulfilled. The fulfillment of the contract includes the exchange of the good specified in the contract and the transfer of money (i.e., the price specified in the contract).

Even after the execution of these four steps for both phases, some sellers still might want to sell goods, and some buyers might have unsatisfied needs. For this reason, the execution of the two phases is repeated six times, with a growing search radius on the buyers' side.

2.2.4 Model validation

To validate the model, we applied multiple techniques:

- The model's structure, execution algorithms, and simulation results were discussed in expert workshops.
- The model was based on and calibrated with empirical data, both quantitative and qualitative (as suggested by Boero and Squazzoni, 2005; Louie and Carley, 2008; or Schutte, 2010).
- A parameter sensitivity analysis was performed.
- A set of sample agents was tracked throughout the simulation.
- The integration of visual output into the simulation, or "visual debugging" (Grimm, 2002), was used to both display dynamically changing trading relations and chart important output parameters.
- The model was documented using the standardized ODD protocol (Grimm et al., 2006, 2010).

A further modeling technique worth mentioning, which we did not apply, is ordinal pattern analysis (Thorngate and Edmonds, 2013). If data are available, they can be matched with simulation output using ordinal pattern analysis, which allows testing ordinal predictions gained from hypotheses against a set of observations. However, authors such as Oreskes et al. (1994) also claim that validation of open systems (e.g., our model), in a strict sense, is not possible at all.

2.3 Scenario simulation

Two sets of scenarios demonstrate the use of the proposed model for explorative inspection of different market situations. The simulation by no means attempts to predict the behavior of real markets; rather, we present the model's explanatory power by describing its complex behavior. In each scenario we vary only a single, initial parameter.

We introduce two simple measures that indicate the availability of wood fuel from the producers' and consumers' points of view. The AAC utilization rate (AUR) is:

$$\text{AUR} = \frac{\text{Amount of wood made available on the market}}{\text{Amount of wood available by the AAC}} \quad (2.2)$$

The AUR shows the quantity of wood made available on the markets by wood producers with regard to the theoretically available quantity given by the AAC. A maximum value of 1 indicates that the AAC is exhausted to its full extent by the wood producers. All values less than 1 mean that a certain amount of wood remains unused in the forests. In the long run, the AUR cannot surpass 1, because otherwise, wood production would be non-sustainable. In the short run, the AUR can temporarily exceed 1, if unused AAC contingents from the past are used.

Whereas the AUR is helpful to assess wood production, the availability of wood on the consumers' side can correspondingly be measured by the supply rate (SR):

$$\text{SR} = \frac{\text{Quantity of wood bought by consumers}}{\text{Quantity of wood needed by consumers}} \quad (2.3)$$

The SR can be calculated as an average for whole classes of agents or for individual agents. A maximum value of 1 indicates that a certain agent class (or individual agent) can completely fulfill its demand for a good. All values less than 1 mean that at least some consumer agents are left unsatisfied. In general, this state is not a problem in the short run, because all consumers have a certain stock of the desired good to use, but in the long run, it may cause agents to exit the market.

Each of the following scenarios represents an average of 100 simulation runs with the exact same initial parameter setting but varied initial random seeds. After starting from their initial values, certain dynamically changing parameters such as prices require some time to arrive at a level that is specific to a single simulation run. In all scenarios, the simulation needs three to five years to overcome the initial calibration phase. Therefore, unless otherwise stated, we excluded the first five years from the computation of the sums, averages, and so forth.

The simulated absolute levels of prices or quantities traded depend heavily on the simulation's initial parameter choice. Data on how to set the parameters are not available, nor is there any such thing as an ultimately "correct" parameter choice. Therefore, of more interest than absolute numbers are their relationships and their relative development.

2.3.1 Base scenario ($S_{2.6}$)

In the base scenario ($S_{2.6}$), initial total supply equals initial total demand of both roundwood and wood fuel. The forest growth rate is a parameter set at the beginning of the simulation, which indicates the growth rate of trees in the forest per year. We measure it as the new amount of wood added to the (old) total amount of wood each year. In the base scenario, this parameter is set to 2.6%. The initial number of simulated agents per class is set as described in Table 2.1. While Fig. 2.4 shows a map of the chosen sample region during a single run at a certain point in time, Fig. 2.5 shows a Sankey diagram with the simulated aggregate average roundwood and wood fuel flows in m^3 between sellers and buyers in years 5-20.

Foresters produce and sell much more roundwood and wood fuel than private forest owners. Furthermore, wood consumers' aggregated monthly demand, as Table 2.1 shows, corresponds to the quantities bought. Note that for small wood fuel consumers, private forest owners as a source of wood fuel are more important than they are for big wood fuel consumers. Small private wood fuel consumers cover 39% of their needs through private forest owners and 42% through foresters. In contrast, pulpwood consumers obtain only 5% from private forest owners and 71% from foresters. For the rest of the wood fuel consumers, the ratios are roughly 10% and 72%. The reason is that large consumers in general, if the supplier is a small one, give poorer values to the quantity component of the profit criterion during the trading deal selection process using AHP.

2.3.2 Example 1: Supply variation scenarios

In our first set of scenarios, we explore the effects of a varied supply on the market. How does a situation of scarce or excess supply affect the market? Scenario $S_{2.6}$ is the base scenario, with a forest growth rate of 2.6% (100% of 2.6%). Scenarios $S_{1.3}$ and $S_{1.95}$ are situations of scarcity, in which the forest growth rate reduces to 1.3% (50% of 2.6%) and 1.95% (75% of 2.6%), respectively. Scenario $S_{3.9}$ represents a situation of excess supply, with a forest growth rate of 3.9% (150% of 2.6%). We are not yet concerned about whether such diverse growth rates are realistic, but we attempt to illustrate clearly the effects of scarce and excess supply. In all scenarios, we adapt the AAC to the changed forest growth rate. We initially set all other model parameters to the exact same values for each scenario. Because, as mentioned previously, the short-term demand for wood is constant but the short-term supply is not, an excess or scarcity situation can occur in the short run

Fig. 2.6 shows the development of the roundwood and wood fuel prices (in CHF/ m^3 ; panels a and c) and the aggregated consumption (panels b and d) per month in the four scenarios. In general, consumption is the highest and prices are the lowest in scenario $S_{3.9}$, a situation of excess supply. Conversely, consumption is the lowest and prices are the highest (until year 12) in $S_{1.3}$, a situation of scarce supply. Scenario $S_{1.95}$ is somewhere in between $S_{1.3}$ and $S_{2.6}$.

In the years 11-14 in scenario $S_{1.3}$, the roundwood market crashes. The scarcity of roundwood is so extreme that many sawmills are forced to exit the market. The

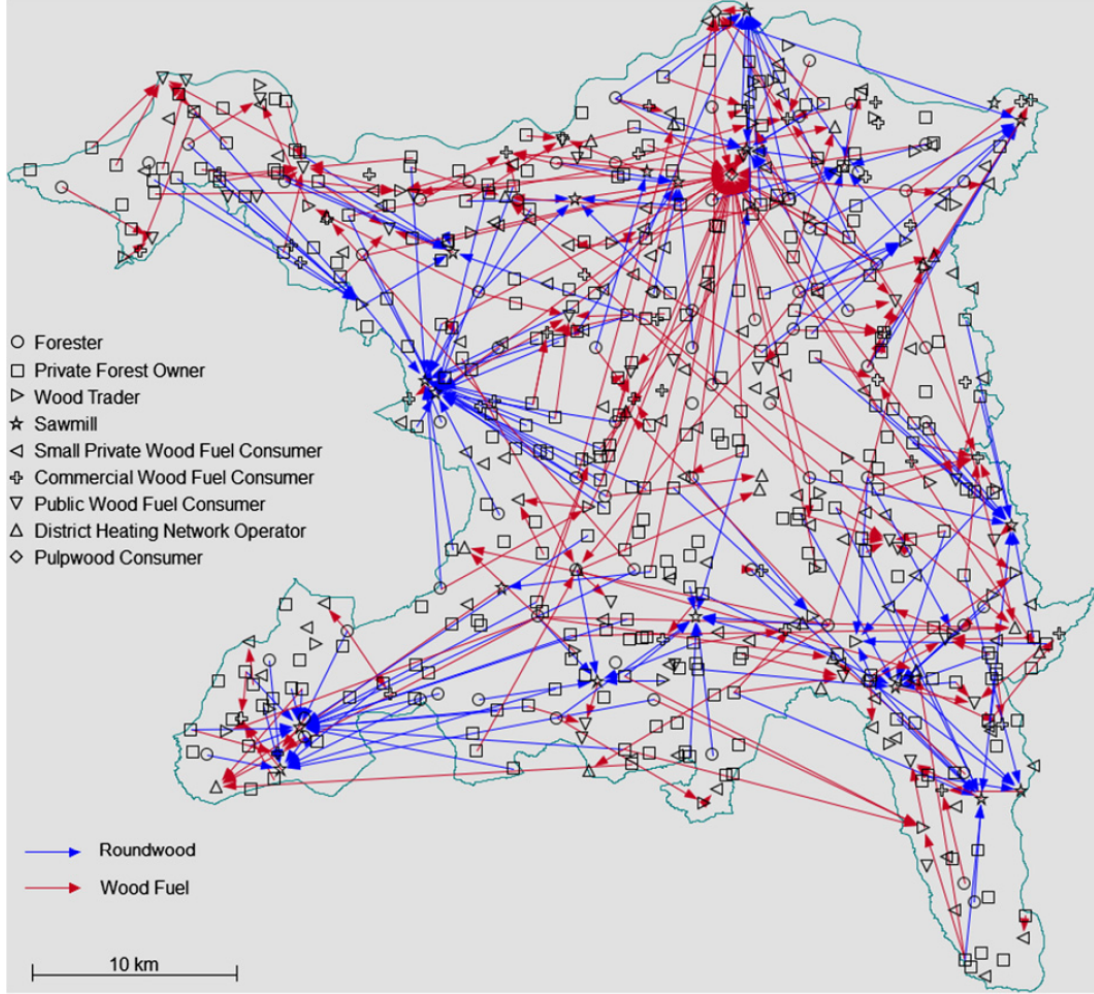


Figure 2.4: Map of active trading relationships at a certain point in time during a single simulation run. Different shapes represent different agent classes. Arrows indicate executed trades with the seller at the arrow's beginning, with the buyer at its head. Roundwood trades appear in blue and wood fuel trades in red. One pulpwood consumer is clearly recognizable by its high number of active wood fuel trades over a larger distance. Also several sawmill agents are indicated by a large number of blue arrows pointing towards them.

roundwood price crashes (panel c) as the demand for roundwood decreases significantly (panel d). Fig. 2.7 shows the development of demand for wood fuel as a stacked bar chart and the development of demand for roundwood as an overlaid single line for scenario $S_{1.3}$. In years 9-13, the demand for roundwood decreases. It reaches a minimum in years 13-15, from which it then recovers. Especially pulpwood consumers are sensitive to situations of under-supply (Fig. 2.7), because they are very few, but large agents. They are forced to exit the market in years 8-10.

Fig. 2.8 provides an overview of the WFM ratio (formula 2.1), the AUR (formula 2.2), and the SR (formula 2.3).

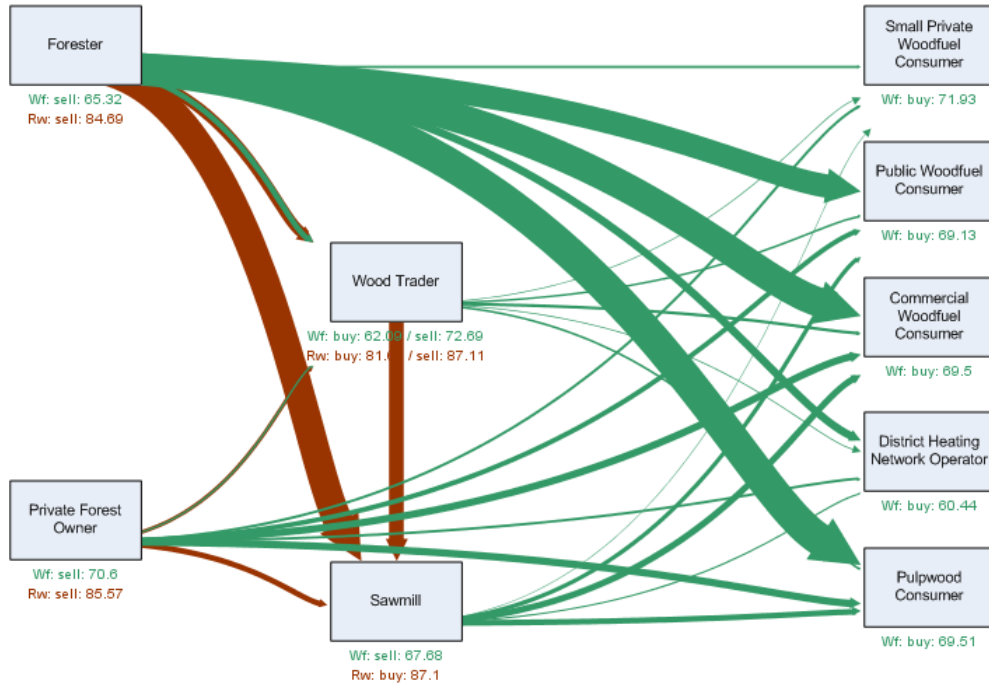


Figure 2.5: Sankey diagram of the simulated aggregate average wood flows between suppliers and demanders in the base scenario (S_{2.6}). Brown arrows indicate roundwood flows, and green arrows indicate wood fuel flows. The thickness of an arrow is proportional to the average traded wood quantities between different classes of supplier and demander agents. The figure also shows the emerging average prices asked/paid by agent classes (all in CHF/m³ wood). "Rw sell" is the price asked for roundwood by a class of supplier agents, and "Rw buy" is the price bid for roundwood by a class of consumer agents. Accordingly, "Wf sell" and "Wf buy" are the corresponding prices for wood fuel. Wood traders can buy wood at special conditions from foresters and private forest owners.

Wood fuel consumers can more or less collectively satisfy their demand in scenarios S_{1.95} and S_{3.9}, but less so in S_{2.6} and definitely not in S_{1.3} (Fig. 2.8, panel f). In S_{1.3}, there is simply not enough wood on the market. The AUR (Fig. 2.8, panel h) is only low as an average figure because of the market breakdowns in years 11-14 (cf. Fig. 2.6). Otherwise, it would be the highest of the given scenarios.

In S_{1.95}, because of the higher forest growth rate, more wood can be produced, and because wood prices are also relatively high (Fig. 2.6, panels a and c), the AAC is fully exhausted (Fig. 2.8, panel h). At the same time, wood producers tend to produce less wood fuel in favor of roundwood (Fig. 2.8, panel g).

In S_{2.6}, even more wood is offered on the market in absolute terms, and therefore the markets have become so attractive for wood fuel consumers that many new ones enter the market. At the same time, win margins become lower for wood producers, and some private forest owners are no longer motivated to produce wood. Thus, the

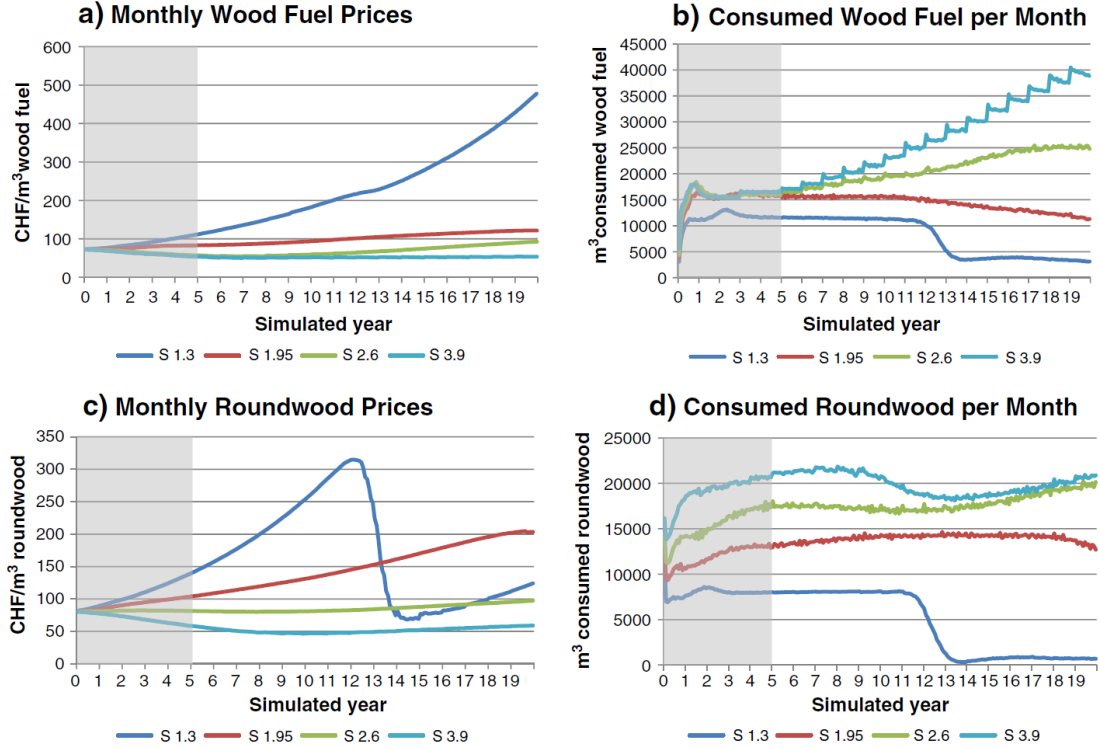


Figure 2.6: Development of simulated wood fuel and roundwood prices and consumption in four scenarios. The first data points shown in the diagrams are the results after one month of simulation, so consumption levels in panels b and d might appear to vary initially, though for all scenarios at the simulation's beginning, they are set to the same initial values.

e) S_{1.3}: Aggregated Monthly Rw and Wf Demands

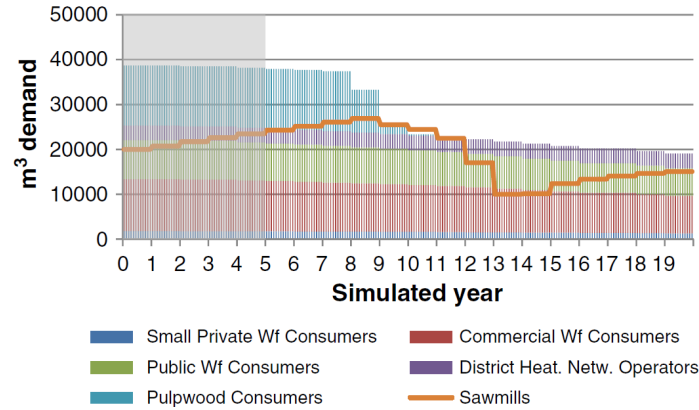


Figure 2.7: Development of the aggregated monthly roundwood (orange line) and wood fuel (colored stacked bars) demands over time in scenario S_{1.3}.

AUR is slightly lower than in S_{1.95} (Fig. 2.8, panel h). The combined effect is a slightly reduced SR in S_{2.6} compared with S_{1.95} and S_{3.9} (Fig. 2.8, panel f).

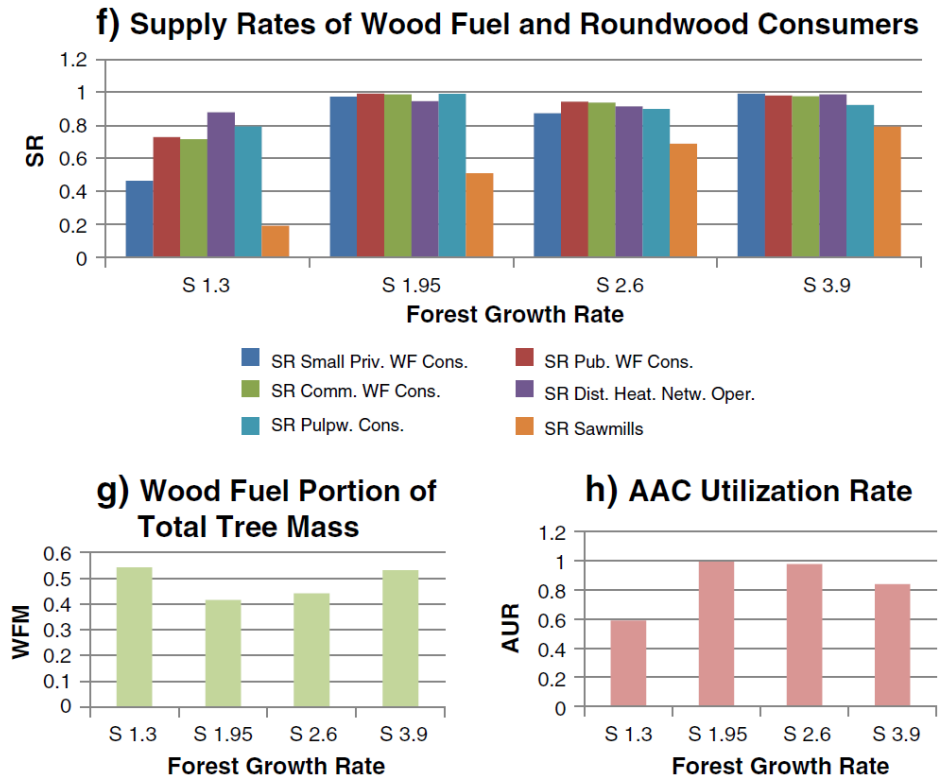


Figure 2.8: f) SR for wood fuel consumers, g) WFM rate, and h) AUR in four scenarios: S_{1.3}, S_{1.95}, S_{2.6} and S_{3.9} (years 5-20).

In S_{3.9}, because of the excess supply, prices tend to be the lowest (Fig. 2.6, panel c), and market entry resulting in rising demand the fastest. Even more private forest owners stop producing wood in this case, and thus the AUR is lower than in S_{2.6} (Fig. 2.8, panel h).

Roundwood consumers, however, cannot satisfy their demand fully in any of the four scenarios (Fig. 2.8, panel f). Accordingly, we might expect roundwood consumers to leave the market and demand to drop in all three scenarios, which is not the case. Rather, it is caused by the assumptions of the sawmill agents' cost structure, in combination with a modeled guaranteed disposal of timber products on the (external) timber product market. On the one hand, in the model the relatively low fixed costs lead to a low pressure on high capacity utilizations. On the other hand, sawmills sell their products to the timber products market, which is modeled purely exogenously. Therefore, whatever amount of wood products they produce, they can always sell them on the timber products market. Whereas competitive forces are modeled regarding the productive input of roundwood consumers, no such forces exist in the model for productive output.

The effect of suboptimal roundwood supply for sawmills in Switzerland can indeed be observed in reality as Pajarola (2009), relying on Pauli et al. (2003), states. According to Pajarola (2009), reasons for suboptimal capacity utilization are related to high transport and harvesting costs.

2.3.3 Example 2: Demand variation scenarios

In a second set of scenarios, we explore the effects of varied demand on the market. This time, the initial number of roundwood consumers varies, starting with a simulation with 0 sawmill agents in scenario S_0 , 5 in scenario S_5 , 10 in S_{10} , and so on, up until 40 sawmill agents in scenario S_{40} . All other initial parameters are set as in the base scenario (which, if added, would be located between S_{20} and S_{25}). So we address the key question: What is the optimal number of roundwood consumers on the market from the perspective of:

- i. roundwood consumers, desiring roundwood prices to be as low as possible;
- ii. wood fuel consumers, desiring wood fuel prices to be as low as possible; and
- iii. policy makers, needing to maximize a (sustainable) wood consumption level across the market?

In Fig. 2.9, panel a shows the average monthly roundwood prices, while panel b shows the SR of sawmills. From the perspective of roundwood consumers, being the only one (monopsony on the roundwood market) is desirable, because prices are the lowest (Fig. 2.9, panel f) and the SR is the highest (Fig. 2.9, panel b) as a result of the complete lack of competitors.

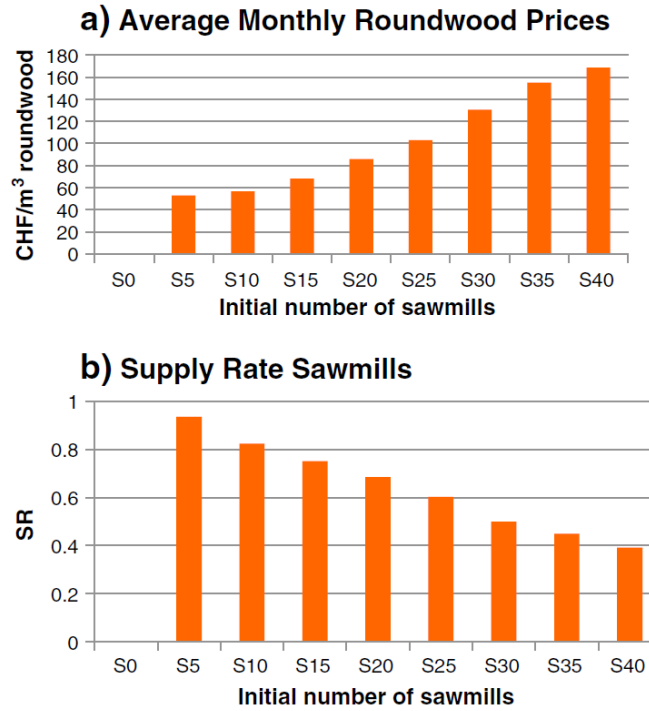


Figure 2.9: Average monthly roundwood prices and SR for sawmill agents in nine scenarios: S_0 - S_{40} (years 5-20).

Fig. 2.10 shows the wood fuel consumers' perspective. If there are few roundwood consumers in the market (S_0 - S_5 in Fig. 2.10, panel c), not enough wood fuel gets produced, resulting in high wood fuel prices above 100 CHF/m³. Competition for the

2.3. SCENARIO SIMULATION

scarce good is fierce, although the WFM reaches a maximum value of 0.6 (S_0 - S_5 in Fig. 2.10, panel e). To achieve the lowest wood fuel prices, an initial number of 10-15 roundwood consumers is required (S_{10} - S_{15} in Fig. 2.10, panel c). Fig. 2.10, panel d, depicts the SR: An SR slightly greater than 1 can occur in the short run but not in the long run. A minimum of five sawmill agents (S_5) is necessary to reach more or less satisfying levels for all wood fuel consumer classes.

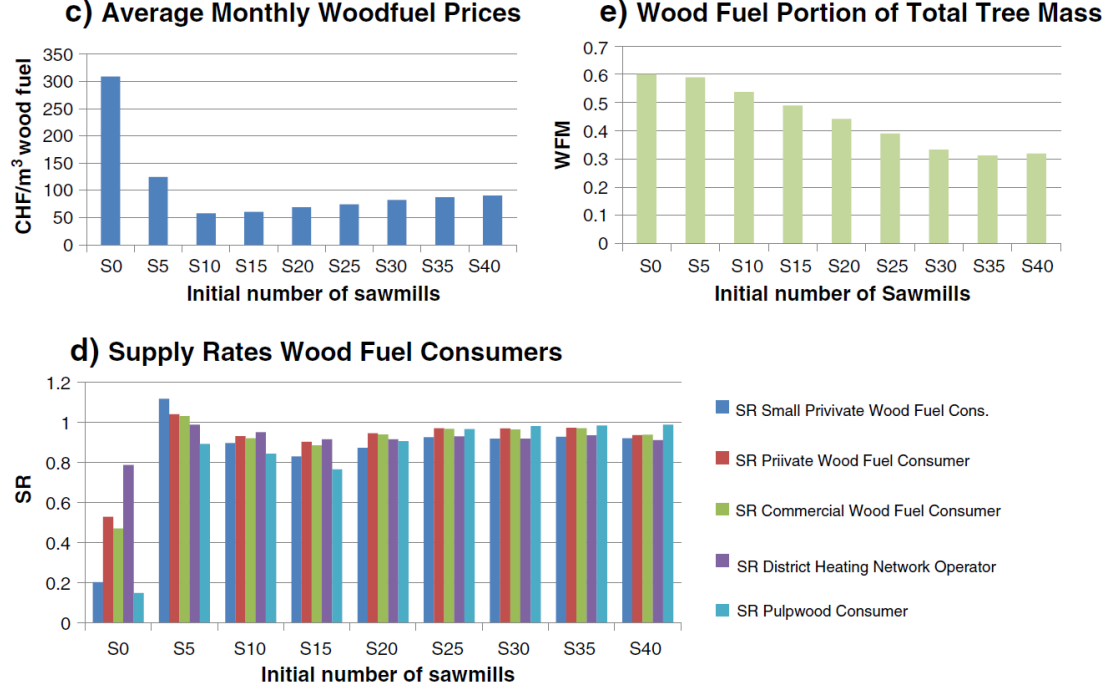


Figure 2.10: c) Average monthly wood fuel prices, d) SR of wood fuel consumers, and e) WFM in nine scenarios (years 5-20).

Fig. 2.11 reflects a policy maker's perspective. If the goal is to maximize overall (sustainable) wood consumption on the market, between 25 and 30 sawmill agents are preferable, because at this level, the quantity of consumed wood is the highest (S_{25} - S_{30} , Fig. 2.11, panel f), and the AUR levels are close to 1 (Fig. 2.11, panel h). A higher initial number of sawmills (S_{35} - S_{40}) forces more sawmill agents to exit the market because of unaffordable roundwood prices. For completeness, the consumption levels of wood fuel (Fig. 2.11, panel g) and roundwood (Fig. 2.11, panel h) are also given. On the one hand, to maximize the level of consumed wood fuel individually, between 10 and 20 sawmills are optimal (S_{10} - S_{20} , Fig. 2.11, panel g). On the other hand, to maximize the level of consumed roundwood individually, between 30 and 35 initial sawmill agents are optimal (S_{30} - S_{35} , Fig. 2.11, panel i).

The conclusion to be drawn here is that no single optimal initial number of sawmill agents can satisfy the interests of all stakeholders. A higher initial number of sawmill agents leads to higher levels of roundwood consumption (Fig. 2.11, panel f) and competition among roundwood consumers, which in turn prompts higher prices (Fig. 2.9, panel a) and lower roundwood SR (Fig. 2.9, panel b). A minimal initial number of sawmill agents is required to achieve a satisfying level of wood fuel production and

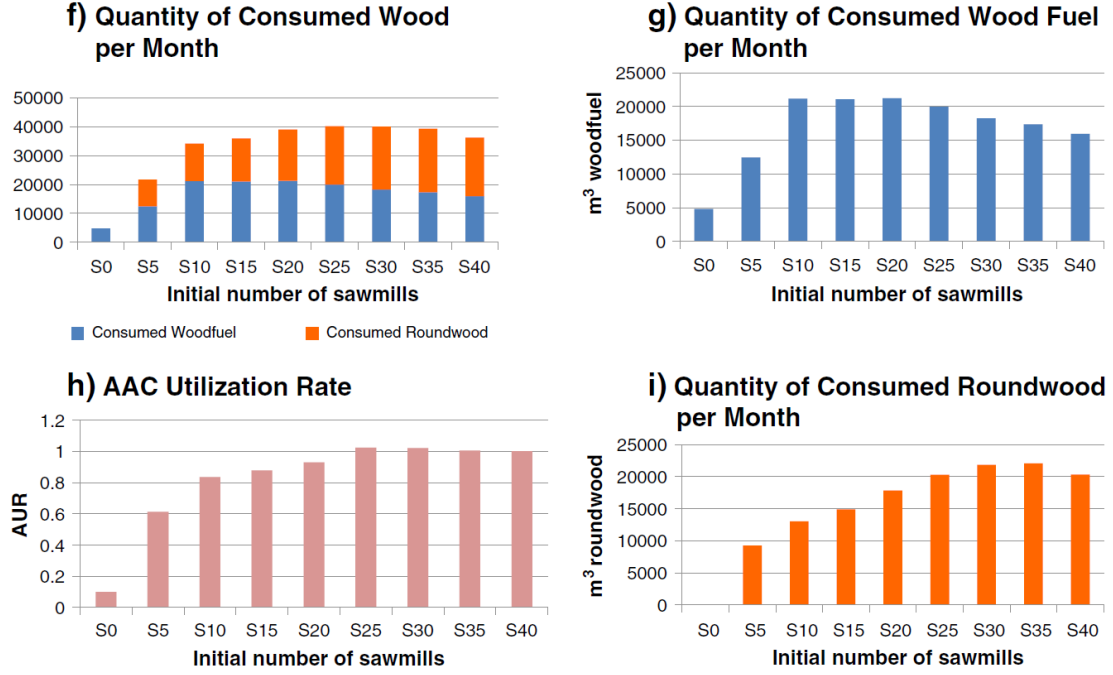


Figure 2.11: Summed and individual consumed wood fuel and roundwood quantities per month and AUR in nine scenarios (years 5-20).

affordable wood fuel prices (Fig. 2.10, panel c). Yet the two optima do not necessarily coincide with the one that leads to maximal total wood consumption (Fig. 2.11, panel f).

2.4 Discussion

2.4.1 Interpretation of the scenarios

The supply variation scenarios confirm some basic economic assumptions about markets, such as that a scarce supply leads to higher prices and lower consumption, whereas excess supply has the opposite effects. More advanced analyses, such as aggregation by agent class or even agent type, are possible too. For example, as Fig. 2.7 shows, the class of pulpwood consumers is especially vulnerable in a situation of extreme scarcity, more so than other classes of wood fuel consumers. One reason is that their win margins are especially low, compared with those of other wood fuel consumers, due to strong competitive forces. In addition, the markets' behavior can be nonlinear or even discontinuous, as in the observed breakdown in $S_{1.3}$. Multiple overlapping effects and the existence of threshold values can cause output parameters to behave in hard-to-predict ways. For example, though the average demand is highest in $S_{3.9}$ (Fig. 2.6, panels b and d), the AUR is not necessarily (Fig. 2.8, panel h). As explained previously, this result is mainly due to the presence of inactive private forest owners with activity threshold values.

The demand variation scenarios demonstrate how the model enables more complex analyses as well. Different stakeholder groups can have competing interests, and often no single optimum situation exists for a given problem. Wood fuel consumers might be interested in a market structure with a large number of sawmills, because it increases wood fuel availability. Yet it also increases competition among roundwood consumers and therefore might be contrary to their interests. In such a situation of coupled markets the interdependencies can become quite complex and therefore difficult to manage from a policy maker's point of view. A consolidation of roundwood producers can be observed as a long-term trend in Aargau and Switzerland, there are nowadays fewer but bigger roundwood producers in business than during the mid 1990s (BFS (Swiss Federal Statistical Office), 2012a,b). Additionally, in the same time the interest in using wood fuel as an alternative energy source has increased. It would require a more in-depth investigation to come to a conclusion on what the effect of these combined developments is on the markets under different oil price developments.

Not shown in the scenario analysis are micro-level analyses (individual agent behavior), though these are theoretically possible, assuming the produced amount of data can still be handled. An example with scenarios focusing more on agent behavior is available in Kostadinov et al. (2012).

2.4.2 Model boundaries

There are different applicable criteria regarding how to set a market's scope or model boundaries; the choice should match the model's purpose. For the reasons we described in Section 2.2, we chose to focus on the Swiss canton Aargau, which had several consequences. Whereas in Switzerland, the geographical horizon of most small to mid-sized wood fuel consumers does not exceed a few kilometers, big consumers (e.g., pulpwood consumers) buy wood fuel on international markets. For big wood fuel consumers, being located inside Aargau's borders might constitute an artificial geographical boundary, whereas for smaller consumers, it usually does not.

On the roundwood markets, the relevant geographical scope depends more on the product segment. Low quality, mass segment roundwood is mostly traded inside the canton's or country's borders, yet it is not uncommon for high quality products to be shipped internationally. However, Pajarola (2009), relying on Pauli et al. (2003), points out that in Switzerland, wood is mostly harvested in municipalities and then sold to local sawmills. Again, setting the model's scope equal to canton Aargau's borders might not result in a fully appropriate geographical size for all cases, but it should be sufficient for the majority.

One of our basic intentions was to reach a better understanding of the market participants' behavior and interactions. This goal affected our choice of canton Aargau, because this model scope still enabled us to conduct qualitative interviews with market participants close to us. We plan to increase the model boundaries and include several cantons, and if possible the whole of Switzerland, once we resolve some performance issues.

2.4.3 Traded goods

The selection of goods being traded must take into account the model's purpose. In our case, a differentiation of roundwood and wood fuel was sufficient. For other purposes, it might be necessary to distinguish varying product qualities or between hard and soft wood. The needs of consumers applying wood fuel to energetic use also might diverge to some extent from consumers from the pulp and chemical industries. Furthermore, because harvesting hard and soft wood usually results in significantly different roundwood-to-wood fuel ratios (WFM), we calibrated the model with regard to canton Aargau's relative shares of hard and soft wood. Both roundwood and wood fuel traded in our model therefore represent "averaged products."

2.4.4 Agent classes and types

In accordance with the roundwood and wood fuel markets, we required at least one consumer agent class for each market. We prioritized modeling the wood fuel consumers, so there are more wood fuel consumer classes than roundwood consumer classes. For the agent typification, statistical classification algorithms might be used, but these required data were not available, so we relied on qualitative interviews instead.

2.4.5 Agent behavior

A key finding was the importance of the qualitative interviews conducted with market participants and especially non-industrial wood producers. The resulting data supported many of the findings of studies presented by Beach et al. (2005); Bohlin and Roos (2002), and Conway et al. (2003). Similar alignment might not arise for markets in which industrial wood production is predominant.

It is difficult to judge whether AHP is an adequate tool to describe market actors' decision behavior. We assume that for decisions made rationally and consciously, AHP might be adequate, whereas decisions based mainly on gut feelings might be more random in nature and thus not be adequately represented by AHP. There exists no single, agreed-on, best practice in the ABM community regarding how to implement human decision behavior algorithmically. Alternative, complementary approaches include the physis, emotion, cognition, and social status (PECS) model (Urban and Schmidt, 2001) or the belief, desire, intention (BDI) software model (Georgeff et al., 1998). This is one of the issues we would like to address in further studies more in depth.

2.4.6 Negotiation protocol

We faced difficulties with regard to how to model a geographically distributed interaction and negotiation protocol, where agents are located in space (or, more abstractly, on a plane), rather than meeting with all other agents in a virtual marketplace (a point). A geographically distributed negotiation protocol is closely related to agents' social network. We solved this issue by introducing the phone books (see "Agents and agent classes" section) and extending each agent's search radius incrementally when it

remained dissatisfied with the outcome of a negotiation phase. Another difficulty was that wood traders act as both buyers and sellers of roundwood and wood fuel, and our suggested protocol needed to map these dual roles.

Defining the agent interaction protocol is perhaps the most important modeling step of ABM. Different negotiation protocols might lead to different simulation outcomes, but replacing one protocol with another for testing purposes is usually impossible, without having to rewrite substantial parts of the simulation code. In many financial market models, auction protocols serve to model interactions between agents; Pellizzari and Dal Forno (2007) compare the effect of different auction protocols to the simulation outcome of a clearly defined financial market. Auctions come close to the observed interaction between market participants in most financial or securities markets. Furthermore, in Switzerland, very high quality roundwood is often sold through on-site auctions, but medium to low quality roundwood and wood fuel is not. The suggested negotiation protocol thus represents the observed interaction between market participants better than an auction. Whereas for technical multi-agent systems, prior studies suggest a variety of negotiation protocols, the same cannot be said for ABM of human social systems.

2.5 Conclusions

We have presented an agent-based model of a Swiss wood market. With ABM, we can combine several important peculiarities of Swiss wood markets in a single, coherent modeling approach:

- *Agent decision behavior and interaction:* Other than price, factors such as friendship and mutual trust, as well as market participants' personality types, play a major role in the business relations between wood producers and consumers. Modeling individualized decision behavior and relations is one of ABM's core strengths. We added a friendship criterion in the agent decision process and assigned a corresponding friendship value to the agents' social networks. Agent types were modeled with varying weights applied to criteria in the AHP.
- *Market interdependencies and feedback loops:* Although wood production focuses on roundwood as its main product, wood fuel is a valuable side product. Markets for both goods are linked through temporal, spatial, and economic feedback loops, so a simulation approach such as System Dynamics or ABM is appropriate. We combined the sequential execution of the two markets, such that wood producer agents adjusted their relative output of both goods (WFM) and adapted market entry/exit thresholds. As a result, we could observe feedback loops in the sample scenarios.
- *Wood production constraints:* Wood production in Switzerland can adapt to significant increases in demand only to a limited extent, even in the long run. An upper bound for harvesting set by the AAC, limitations in space and territory, technological advances, ecological concerns, and a political agenda must all be

considered when analyzing the long-term availability of wood. Our model covered some but not all of these aspects.

- *Spatial distribution of wood production and consumption:* A spatial distribution of production and consumption is explicitly, though simply, modeled; we have presented a corresponding negotiation protocol.

However, these points also turned out to be the most difficult ones to solve.

First, the definition of the model boundaries was challenging. In a first attempt, we chose the geographical boundaries of the canton of Aargau as the model boundaries. Yet not all wood produced inside Aargau is also processed in its geographical boundaries. Large sawmills in adjacent cantons buy wood from suppliers in Aargau. We hope to address this issue in further work by both increasing the model size and more fundamentally rethinking the criteria for defining such boundaries.

Second, with regard to geographical and territorial limitations, more realistic model assumptions might result if we could improve on the model's internal geographical representation, especially on transport routes.

Third, as we have argued, we offer no recommended best practices regarding how to model the decision-making processes of market participants and their interaction or negotiation algorithmically. A further, perhaps even more important problem is that empirical data on market participants often are not available and must be gathered. We plan to collect more empirical data about market participants' decision behavior, their individual preference structures and utility functions, and the operational cost structures both on the supplier and consumer side. To do so, we will use companion modeling (Bousquet, 2005), laboratory experiments and role-playing games. Overall, considering these options for further research, we remain convinced that ABM is worthy of further pursuit.

Acknowledgments

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Enhancing Agent-based Models with Discrete Choice Experiments

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Abstract

Agent-based modeling is a promising method to investigate market dynamics, as it allows modeling the behavior of all market participants individually. Integrating empirical data in the agents' decision model can improve the validity of agent-based models (ABMs). We present an approach of using discrete choice experiments (DCEs) to enhance the empirical foundation of ABMs. The DCE method is based on random utility theory and therefore has the potential to enhance the ABM approach with a well-established economic theory. Our combined approach is applied to a case study of a roundwood market in Switzerland. We conducted DCEs with roundwood suppliers to quantitatively characterize the agents' decision model. We evaluate our approach using a fitness measure and compare two DCE evaluation methods, latent class analysis and hierarchical Bayes. Additionally, we analyze the influence of the error term of the utility function on the simulation results and present a way to estimate its probability distribution.

3.1 Introduction

An inherent advantage of agent-based modeling is the possibility to model each agent individually, which makes it a promising method to investigate market dynamics. Simulating the modeled individuals permits emerging behavior to be explored (Kelly et al., 2013). Crucial to developing an agent-based model (ABM) is creating agents that are valid representations of their real-world counterparts. Until a few years ago, not many models in the ABM literature had a strong empirical foundation (cf. Janssen and Ostrom, 2006; Wunder et al., 2013). Even when there was empirical foundation, the empirical data was often collected and integrated ad hoc, i.e., without reference to a

defined methodology. However, in recent years great efforts have been made to increase the empirical foundation of ABMs, including step-wise descriptions of methods guiding from semi-structured stakeholder-interviews to implemented ABMs (Elsawah et al., 2015).

To further improve this situation, we present an approach where we have applied discrete choice experiments (DCEs) to elicit preferences of actors that are later represented as agents in our model. The term DCE is used according to the nomenclature for stated preference methods proposed by Carson and Louviere (2011). We demonstrate the potential of this approach with a case study of the Swiss wood market. The DCE was conducted with roundwood suppliers to quantify the decision model of the supplying agents. We present two approaches, latent class analysis and hierarchical Bayes, to evaluate the DCE data and show advantages and disadvantages of each approach to parameterize the model. The decision model is based on random utility theory and therefore contains a deterministic component, namely utility obtained through the DCE, and a random component accounting for non-measurable factors of an individual's decision. We present a method to estimate the probability distribution of this random component and analyze its influence on the simulation results.

The Swiss wood market is a suitable market to explore the approach because importance of personal relationships between traders is above average for trading within the market (Kostadinov et al., 2014). DCEs are particularly useful for identifying the personal preferences that form and affect such relationships. If the approach proves to be suitable, we will extend our model to simulate scenarios that have been defined together with policy-makers and other stakeholders. It will then be applied to explore the effect of changes such as the market entrance of bulk consumers or subsidies that are introduced to increase wood availability. The project is embedded in a national research program which aims to increase availability of wood and expand its use (SNF, 2010).

3.2 Related Work

In the literature, many ABMs are described that use some kind of discrete choice model in the agents' decision process. The data for the choice models stem from a wide range of sources, in some cases from estimations. However, only a few researchers used DCEs to improve the empirical foundation of their model:

Dia (2002) conducted a DCE with road users to study how they make route choice decisions in traffic jam situations. With his DCE, he looked for socio-economic variables that have significant influence on route choice decisions. After eliminating the non-significant variables, significant variables were applied to characterize agents giving them a corresponding utility function to evaluate route choice options.

Garcia et al. (2007) used a choice-based conjoint analysis (CBC) to calibrate an ABM of the diffusion of an innovation in the New Zealand wine industry. They recruited wine consumers to evaluate their decision making behavior and used the results from the CBC to instantiate, calibrate, and verify their ABM.

Hunt et al. (2007) linked ABMs and DCEs to study outdoor recreation behaviors. They compared the concepts of agent-based modeling and choice models and combined them in a case study. They used choice modeling to derive behavior rules, and used the simulated world of an ABM to illustrate and communicate the results.

Zhang et al. (2011) investigated the diffusion of alternative-fuel vehicles using an ABM approach. They conducted a CBC in conjunction with hierarchical Bayes to elicit the preferences of the consumer agents in the model. They used two utility functions in their model, where one is obtained by the CBC and the other by separate questions in the survey. While the utility function obtained by the separate questions includes an error term, the utility function obtained by CBC does not, which would be required in random utility theory.

Gao and Hailu (2012) used an empirically based random utility model to represent the behavior of angler agents in a recreational fishing model. The behavioral data is based on multiple surveys from different sources. Angler agents choose angling sites based on individual characteristics and attributes of the alternative sites.

Arentze et al. (2013) implemented a social network as an ABM where the probability of a person being a friend with another person depends on a personal utility function. The utility function accounts for social homophily, geographic distance, and presence of common friends. It is based on the random utility model and therefore includes an error term. The authors use a revealed preference method to gather the model data by asking survey participants about characteristics of their existing friendships.

Lee et al. (2014) used an ABM to simulate energy reduction scenarios of owner-occupied dwellings in the UK. The agents in the model were home-owners which had to decide, triggered by certain events, if they want to carry out any energy efficiency improvement in their house. The decision-making algorithm originates in DCE data from two separate studies, where the population was divided into seven clusters with similar preferences. The preferences of the agents in each cluster were distributed around the center point of the cluster to provide a heterogeneous population. The utility function of the agents are deterministic, i.e. without error component.

It is striking that where combinations of ABMs and DCEs are applied in the literature, the role of the error component and how it is modeled are often neglected or at least not explicitly mentioned. However, the error component is central to random utility theory, which is the theoretical foundation of DCEs. This paper contributes to this field by rigorously adhering to random utility theory that underlies the DCE method to improve the empirical foundation of ABMs.

3.3 Description of the Model

This section describes the model according to the ODD + D protocol (Müller et al., 2013), which extends the ODD protocol (Grimm et al., 2006, 2010) to be more suitable for describing the decision-making process of the agents. The focus of this paper is more on the method than on the model; however, as especially the design of the DCE is not separable from its application area, a rough understanding of the model is needed

before the method can be described in detail. This is another reason why the following description aims at giving sufficient information to understand the model, not to enable exact replication.

3.3.1 Overview

3.3.1.1 Purpose

The model represents the wood market in Switzerland and is used to simulate scenarios such as the market entrance of bulk consumers or a fluctuating exchange rate. The goal of these simulations is to identify factors influencing the wood availability on the market. The model is used by the authors, while the simulation results are reported to the appropriate stakeholders.

3.3.1.2 Entities, state variables, and scales

Entities: Entities in the model are different types of agents which act within one or more markets (Figure 3.1). However, to reduce complexity for the reader, we present our approach eliminating all but two agent types from the market. This is possible because the main assortment on the Swiss wood market is roundwood, and there is only one type of consumer on the market for it: sawmills. Two supply agent types exist in the roundwood market, namely private forest owners and public forest managers. Since the majority of roundwood is harvested and sold by public forest managers (hereafter referred to as foresters), the private forest owners are also omitted in this paper. The wood fuel market and the industrial wood market are dependent on the roundwood market, because wood fuel and industrial wood are by-products that accumulate during the roundwood harvesting and production process. These two by-products can be omitted in this paper because they do not have a direct impact on the main product roundwood.

State variables:

- Each agent has a location (x-/y-coordinate) and a portfolio of goods he buys or sells.
- Every agent has a confidence value for each and every contractual partner between which negotiations have taken place. The confidence increases after successful negotiations leading to a contract and decreases if negotiations fail.
- Foresters have a certain monthly harvesting capacity, sawmills have a monthly processing capacity.

Scales: One time step represents one month, simulations were run for 20 years.

3.3.1.3 Process overview and scheduling

A forest year starts in September and ends in August of the following year. Each month proceeds in three steps: in the first step, all agents are shuffled and then one after the

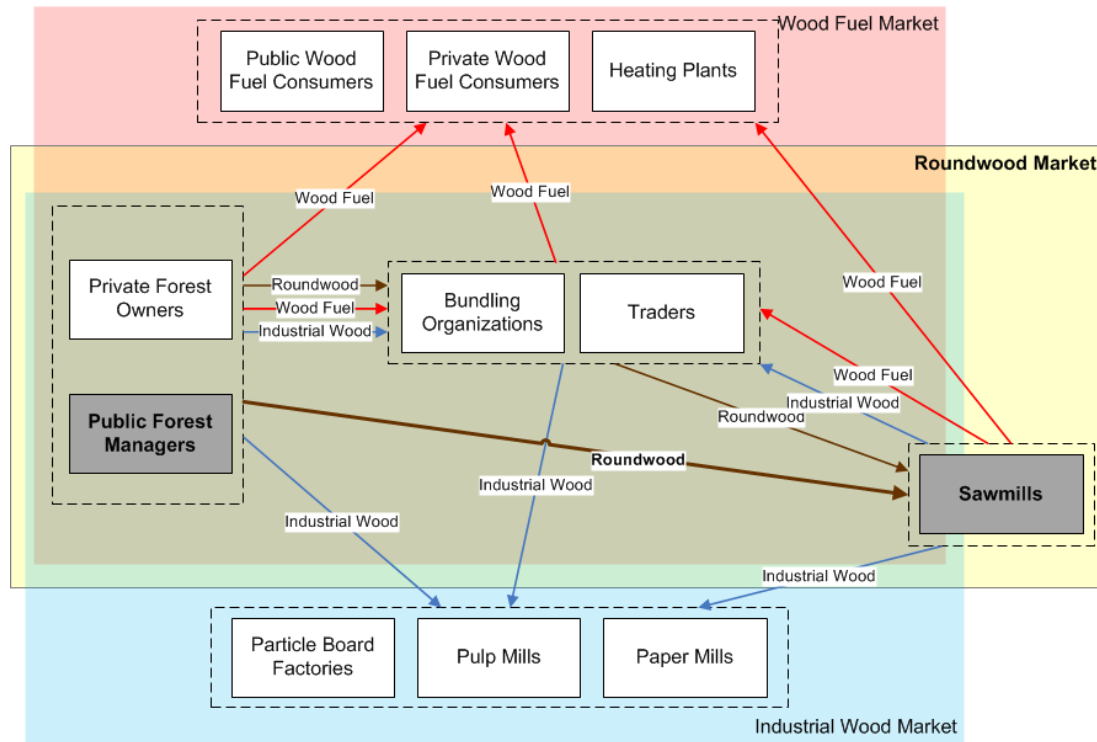


Figure 3.1: Conceptual model of the Swiss wood market with the three assortments wood fuel, roundwood, and industrial wood, and the corresponding sellers, buyers, and intermediaries. To reduce complexity, this paper considers only public forest managers and sawmills.

other negotiates new contracts with other agents. In the second step, foresters prepare their deliveries, i.e. they harvest wood and deliver to their contractual partners. In the third step, sawmills process the wood received from the foresters. This process is also described as pseudocode in the appendix.

3.3.2 Design Concepts

3.3.2.1 Theoretical and Empirical Background

The conceptual model of agents and interactions was created and continuously refined based on semi-structured interviews and workshops with different wood market actors and stakeholders.

The decision model of the agents is based on random utility theory, which is the basis of several models and theories of decision-making in psychology and economics (Adamowicz et al., 1998). Random utility theory is based on the work of McFadden (1974), who extended the concepts of pairwise comparisons introduced by Thurstone (1927). According to random utility theory, a person choosing between multiple alternatives chooses the one with the highest utility, where the utility function is defined as $U = V + \epsilon$, with U being the total unobservable utility, V the deterministic observable

component of the consumer's behavior, and ϵ a random component representing the non-measurable factors of an individual's decision. This error term has a probability distribution that is specific to the product and the consumer. In our model, such a utility function is used by each agent to negotiate new contracts. Agents evaluate incoming and outgoing potential transactions by considering five decision criteria. This leads to the following form of the utility function:

$$U = V * \epsilon = \beta_1 c_1 + \beta_2 c_2 + \beta_3 c_3 + \beta_4 c_4 + \beta_5 c_5 + \epsilon \quad (3.1)$$

Where U is the total utility of a potential transaction, β_1 - β_5 are the part-worth utilities of the five decision criteria, and c_1 - c_5 are the numerical values of the corresponding decision criteria. A potential transaction is acceptable for an agent if its total utility is greater than β_{None} , the part-worth utility of not accepting a transaction, i.e., ΔU must be positive:

$$\Delta U = U - \beta_{None} \quad (3.2)$$

The part-worth utilities of the decision criteria can be assigned to each agent individually, per group of agents, or they can be equal for all agents. Our approach to obtain the part-worth utilities will be explained in the method section.

3.3.2.2 Individual Decision-Making

Agents of different types pursue different objectives:

- Forester agents try to harvest a certain amount of wood during each forest year. The target amount of wood is determined by the annual allowable cut. However, the target amount per month differs greatly between the seasons because of various restrictions such as snowfall in winter and increased risk of logging damages in summer. This is implemented in the model by assigning each forester agent with a minimum, optimal, and maximal monthly harvesting amount that takes seasonal variability into account. The minimum and maximum amounts are attributed to the manpower available to each forester; employees must be kept busy, but also have a maximum working capacity. Therefore, to reach the targeted yearly amount, the foresters harvest an amount of wood each month close to the optimum, while balancing monthly variations. To achieve their objective they continuously plan the coming months in the current forest year and negotiate suitable contracts.
- Sawmill agents always try to maintain sufficient wood stocks for continuous processing. They negotiate new contracts based on their demand, which is almost constant throughout the year, with only minor reductions during periods when less wood can be harvested. They have warehouses to balance the reduced wood availability during certain periods and include the warehouse capacity utilization in their planning processes.

When agents negotiate with potential contractual partners, they have to evaluate the potential transaction to see if it is acceptable or not. For this purpose, each agent considers several decision criteria, which are defined for each agent type.

Forester agents consider the following five decision criteria to evaluate a potential transaction. The criteria were identified in semi-structured interviews and workshops with foresters and other domain experts:

- **Amount of wood available.** Foresters generally try to harvest approximately the amount of wood each year that regrows in a year, but never more. Employees have to be kept busy. Therefore, there is pressure to sell enough wood during the year.
- **Amount of wood demanded.** Larger order sizes reduce transaction costs, but also increase concentration risks.
- **Trust in demander.** On the Swiss wood market, wood is usually traded without written contracts. Furthermore, the exact price paid for the logs is determined based on the measurements at the sawmill.
- **Margin.** The net amount of money a forester receives ($= \text{price} + \text{subsidies} - \text{harvesting costs} - \text{transportation costs}$).
- **Expected price development.** Foresters have some tolerance in the annually harvested amount of wood, i.e., they can adapt the amount based on the expected price development. For example, if they expect rising prices, they can postpone the sale of wood to a later date.

Sawmill agents consider five different decision criteria to evaluate potential transactions. However, they are conceptually similar to those of the foresters:

- **Urgency.** The sawmills must have a constant degree of capacity utilization. Supply bottlenecks can usually be absorbed by the warehouse stock, but stock may not be sufficient especially in the seasons when only little wood is harvested. This can place a high urgency on obtaining additional supplies.
- **Size of order.** Larger order sizes reduce transaction costs.
- **Trust in supplier.** Supplies have to be on time and complete.
- **Price.** Higher prices reduce the margin of the sawmill.
- **Expected price development.** If prices are expected to drop and the warehouse stock is not empty, a sawmill can wait for lower prices until making new purchases.

3.3.2.3 Learning

Learning is not included in the model.

3.3.2.4 Individual Sensing

- Agents know the average market prices of previous months and use this information in their decision process
- If an agent contacts another agent between whom no previous negotiation has taken place, there exists no confidence value for this agent. In such cases the confidence value is calculated by averaging the confidence other agents have with the respective contractual partner. This, in effect, can be considered the reputation of the contractual partner.

3.3.2.5 Individual Prediction

The expected price development in the coming months is calculated using the information about past months' market prices, and is a criterion in agents' decision process.

3.3.2.6 Interaction

Figure 3.2 depicts how agents interact with one another, i.e. how they negotiate a new contract. The interaction is initiated by the requestor, who can be either a buyer or a seller. He sends a request including the assortment, the amount, and the price to a potential contracting party. The contracting party can then either decline the request or respond with an offer. The price and the amount in the offer can be different than in the request. Finally, the requestor has the opportunity to either accept or decline the offer. There are no further rounds of negotiation in a single interaction, as bargaining is unusual on the roundwood market in Switzerland. Therefore, this interaction pattern induces three situations where a decision has to be made. These decisions are made according to the approach presented in the sections "Theoretical and Empirical Background" and "Individual Decision-Making".

3.3.2.7 Collectives

Each agent has a personal address book with potential contractual partners in his nearby area. Aside this, there are no collectives in the model.

3.3.2.8 Heterogeneity

All forester agents have a forest with equal size and have equal harvesting capacity. All sawmill agents have the same processing capacity. Their aggregate capacity corresponds to the amount of wood that forester agents are able to harvest; respectively supply and demand are balanced. In the reduced model presented here, import and export within the modeled region are ignored. The two agent types differ in the criteria they consider in their decisions. The considered criteria are always the same per agent type, but the weighting of the criteria may differ from agent to agent.

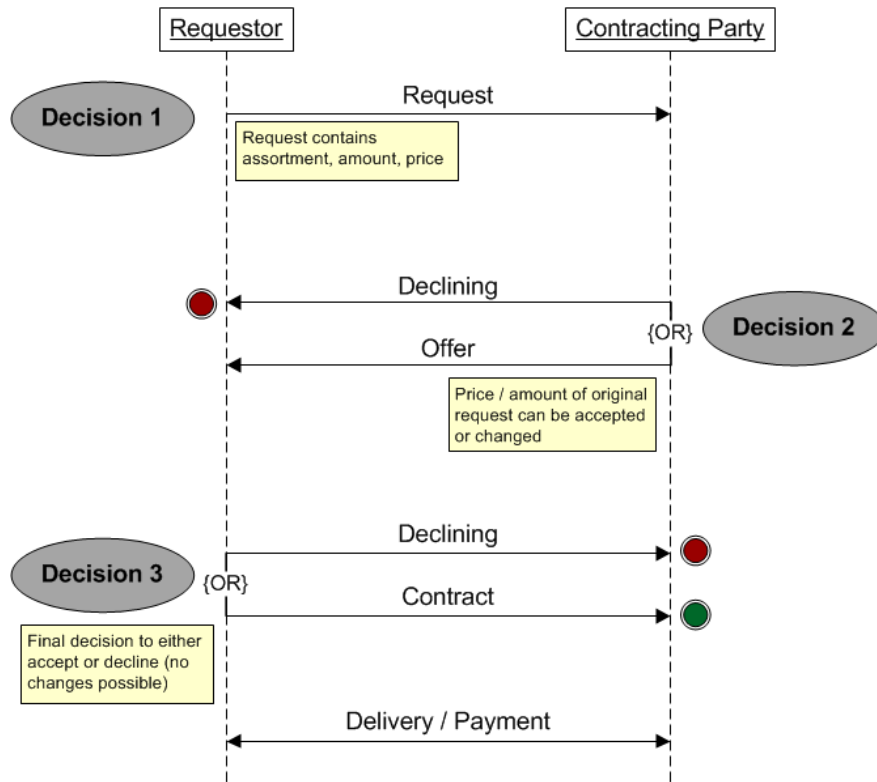


Figure 3.2: Interaction pattern. An interaction is initiated by the requestor, who can be either a buyer or a seller, and results in a contract if buyer and seller reach an agreement.

3.3.2.9 Stochasticity

- The location of all agents is randomly determined during initialization.
- Agents negotiate new contracts in a random order in each simulated month.
- At the beginning of the simulation, agents select potential contractual partners randomly, later they prefer to negotiate with agents they already know from previous contracts.
- As long as agents do not have a contract history, prices are randomly set (Gaussian distribution).
- The utility value calculated in the decision process contains a random component reflected in the error term ϵ , cf. section "Theoretical and Empirical Background".

3.3.2.10 Observation

Several approaches were used to test, analyze, evaluate, and finally validate the model:

- **Evaluation of aggregated results.** A multitude of variables are calculated over all agents for each simulated month. These variables include average, minimum,

and maximum values for prices, traded amounts, monetary situation of agents, etc. The values are stored in a CSV file and are then predominantly evaluated graphically.

- **Evaluation of individual variables for each agent.** Some variables are examined in more detail, i.e., not just minimum/average/maximum values over all agents are recorded, but the specific value for each agent. This is done for variables such as degree of capacity utilization in the warehouse or of production, and also allows the recognition of interesting patterns in the simulation results. This approach uses CSV files as well and was also applied to track a fitness variable which will be presented in the method section.
- **Individual agent evaluation.** This approach traces some randomly selected agents in detail over the whole simulation period. Almost all important data about an agent is stored in an XML file for each simulated point in time, and thus permits further evaluation with a separate evaluation program. For example, this data enables an understanding of the reasons why each and every incoming or outgoing request was accepted or rejected. This approach is especially valuable if bugs are to be traced back to their source.
- **Visual evaluation.** It is possible to run the simulation program with a GUI that includes a map containing all agents. Arrows depict interactions of buyers and sellers live during the simulation. This approach permits a monitoring of agents in their geographical contexts, which would otherwise be difficult using the methods mentioned above.

3.3.3 Details

3.3.3.1 Implementation Details

The model was implemented in Java, a simplified UML class diagram is depicted in the appendix. The model was tested and validated on the one hand with the approaches mentioned in the section "Observation", which are based on face validity (Sargent, 2005) and mainly require the interpretation of graphs. On the other hand, Java assertions were used in many methods to enable continuous testing during the development process. They make it possible to insert preconditions, postconditions, and invariants within the code, making the code easier to read and maintain.

3.3.4 Initialization

A random seed can be set to initialize the simulation permitting the results to be reproducible (cf. section "Stochasticity"), which is an important prerequisite for the validation of a model (Amblard et al., 2007). At the beginning of a simulation run, agents have to conclude contracts with other agents without an available contractual history. Therefore, initially the contract properties such as the contracting party and the price are selected randomly. With a growing contract history from several simulation rounds, agents will attempt to build contracts that are similar to previous

successful contracts. It follows that after an initial phase business relationships become relatively stable (Figure 3.3). This substantiates the observation that over time most business relationships tend towards stability on the Swiss wood market.



Figure 3.3: Number of distinct buyer/seller combinations per month in a 20 year simulation (average of 100 runs). Colored lines represent the final state of an interaction, black lines represent the corresponding 12-month moving averages. It can be seen that after an initial phase of about three years business relationships become relatively stable. In the first three years, there are many requests that do not lead to an offer or a contract. The striking yearly drop of contracts can be explained by the reduction of harvesting activities in summer months.

3.4 Method

3.4.1 Discrete Choice Experiments

To know how individuals make decisions, their preferences need to be elicited. In our case, this implies that the attributes of a potential transaction considered in a decision situation must be known (cf. sections "Individual Decision-Making" and "Interaction"). These attributes and their importances can be identified by means of preference elicitation methods, of which a multitude exist. We concluded that DCEs are most suitable for our case, since they are based on random utility theory (RUT), like the decision model of the agents in our model (cf. section "Theoretical and Empirical Background"). DCEs are stated preference methods; while these have a slightly lower accuracy than revealed preference methods, they have the advantage that an arbitrary number of choice situations can be presented to an individual.

A central point in RUT is the error term. Using the standard choice-based conjoint analysis (CBC) approach that is not based on RUT, evaluating utility functions results

in choice probabilities for different alternatives. However, these choice probabilities are purely based on mathematical theories and not on theories of human behavior or their preferences as in RUT (Louviere et al., 2010). CBC and DCEs both lead to coefficients (also known as "betas") that describe the part-worths of individual attributes for a given target group.

As described in the section "Theoretical and Empirical Background", the error term ϵ of a utility function has a probability distribution that is specific to the product and the individual consumer. This is represented in the model by drawing the error term from a normal distribution that was initialized with a random seed. This seed is based on a combination of (i) the agent's ID, (ii) the ID of the current negotiation with the contract partner, and (iii) the random seed that was used to initialize the simulation. This procedure guarantees that if the same offer has to be evaluated multiple times by an agent, the error term is always the same.

3.4.2 Experimental Setup

In our DCE, only the selling side of the roundwood market was considered. We conducted the experiments with foresters in two Swiss cantons, Canton of Aargau (AG) and Canton of Grisons (GR). We chose these two regions since they show some fundamental differences. First, AG is flat, while GR is mountainous. The mountainous terrain in GR increases harvesting costs, which reduces the profitability of harvesting. There is also a lot of protection forest where harvesting is prohibited entirely. Second, although AG and GR are both border cantons, GR is much more affected by the wood market of the adjacent countries. For this paper we decided to demonstrate our approach only on AG, as this enables us to eliminate the aforementioned peculiarities of GR, which are interesting for the overall study, but would introduce too much noise in the results for the specific purpose of this paper.

Carson and Louviere (2011) categorized the different types of DCEs. Three related approaches are: choice questions (one chooses the preferred option), ranking exercises (all options are ranked), and best-worst choice questions (the best and the worst option are chosen). Foster and Mourato (2002) showed that ranking exercises with larger choice-sets (ranking many options) can lead to inconsistencies in the results. Caparrós et al. (2008) showed that choice questions lead to similar results as ranking exercises that include only the first rank in the evaluation. Akaichi et al. (2013) confirmed this for small choice-sets with only three options.

To avoid the problems of ranking larger choice-sets, we used best-worst choice questions where each question has three options. Best-worst choice questions with three options are similar to ranking experiments. Having exactly three options leads to a complete ordering of the options and thereby increases the number of implied binary comparisons (Carson and Louviere, 2011). Additionally, even though that in a best-worst DCE a respondent is asked for more information than in a DCE where only the preferred option has to be chosen, the cognitive effort is not much higher, as the respondent already evaluated all alternatives in the set to choose the best (Lancsar et al., 2013).

One of the three options presented in our experiment is a "status quo alternative". Having a status quo alternative has the advantage of always offering a feasible choice to the respondent (Carson and Louviere, 2011).

Decision Situation 1 of 12			
Please select the best and the worst option:			
	Option 1	Option 2	Option 3
Amount of wood available	40%	70%	don't sell
Amount of wood demanded	1%	15%	
Trust in demander	0.8	0.2	
Margin	CHF 10	CHF 25	
Expected price development	-10% (decreasing)	+10% (increasing)	
Best option	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Worst option	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

Figure 3.4: Example of a decision situation presented to a subject.

Figure 3.4 shows an example of a decision situation used in our experiment. In each decision situation, the subject had to select the best and the worst options out of three. Two of them were options to sell wood, and one was a "don't sell" option, which was to be chosen if the subject would rather wait for other offers before selling wood. The two selling options each had five attributes, corresponding to the decision criteria explained in the section "Individual Decision-Making", and each attribute could take on three different levels (Table 3.1). All attributes were quantitative, which later facilitates the integration of the DCE results into the ABM. Twelve decision situations were presented to each subject. The influence of such design dimensions – number of attributes, number of levels, number of decision situations – on DCE results have been studied by Caussade et al. (2005). They found that particularly a large number of attributes, but also a large number of levels, have a negative influence on the respondents ability to choose. We considered this point by reducing the attributes and levels to an acceptable minimum. A subsequent study by Rose et al. (2009) showed that the influence of the design dimensions also differs between countries, in particular for the number of decision situations to assess. When Bech et al. (2011) investigated the influence of the number of decision situations on DCE results, they found that even presenting 17 decision situations to each respondent does not lead to problems. However, their results also indicated that the cognitive burden may increase with more decision situations presented. Since we had a relatively low number of potential respondents, we needed to ask as many decision situations per subject as possible, while being careful to not fatigue or even completely discourage the subjects from responding. Therefore we decided that for our study presenting 12 decision situations to each respondent is a reasonable compromise between these two subgoals.

The experimental design (combinations of attribute-levels presented to the subjects) is a controlled random design where all subjects are given different versions of the questionnaire. In this case controlled random design means that the levels are balanced, i.e. each level is presented approximately an equal number of times. Level overlap is

allowed to occur, i.e. in a single decision situation an attribute can have the same level in both options presented.

Attribute	Levels	Explanation
Amount of wood available	70% / 40% / 15%	Amount of wood that has not yet been sold compared to the yearly total amount that can be sold
Amount of wood demanded	15% / 10% / 1%	Size of order compared to the yearly total amount that can be sold
Trust in demander	0.2 / 0.5 / 0.8	1 = highest trust, 0 = no trust
Margin	CHF 25 / CHF 10 / CHF -5	Net margin per m ³ in Swiss Francs
Expected price development	+10% / 0% / -10%	Expected price in a year in relation to current price

Table 3.1: Attributes and levels in the DCE. The selected levels represent typical situations a forester is faced with during a forest year.

3.4.3 DCE Evaluation and Agent Parameterization

There are several methods for evaluating DCEs. We used the following three, because each of them is useful for a specific purpose that we consider valuable for ABMs:

- **Logit.** This evaluation method measures the average preferences of the population by regarding all actors as having equal preferences. This method provides a good starting point to evaluate DCEs, as it gives an overview of the whole population. However, since logit assumes that all agents have equal preferences, much of agent individuality, which is one of the major strengths of ABMs, is lost. The method is described in more detail by Sawtooth Software (n.d.) and Hosmer and Lemeshow (1989).
- **Latent Class Analysis (LCA).** This method divides the sample into several classes of subjects with similar preferences. Using LCA in combination with choice-based conjoint analysis was first proposed by DeSarbo et al. (1995).
- **Hierarchical Bayes (HB).** The individual preferences of each subject in the sample are estimated. This method became popular at the end of the nineties, as it requires much more computational effort as the other two methods mentioned above. Early uses of this method are described by Allenby and Lenk (1994), Allenby and Ginter (1995), and Lenk et al. (1996).

The DCE was designed and evaluated using the Sawtooth 8.3 software. A comparison of this software with other DCE design approaches can be found in Johnson et al. (2013). The evaluation of the DCE leads to a part-worth utility value for each attribute level and one for the "don't sell"-option, the none-option. Therefore three values for the

part-worth utilities are obtained per attribute, one for each level. A linear regression leads to the coefficients of V , the deterministic observable part of the utility function (cf. Equation 3.1). While the betas are obtained from the DCE, the error term ϵ is randomly generated during simulation. It has a mean of zero and a variable standard deviation. An approach to calculate the standard deviation is presented in the next section.

For privacy reasons, the forester agents have random locations that do not conform to the real locations of the corresponding DCE subjects. We assume that this is acceptable, since we do not see any considerable regional distinctions in our study region where this procedure might introduce errors. Additionally, we repeated our simulations multiple times mapping the DCE data differently each time, which should further reduce potential errors.

3.4.4 Estimating the Standard Deviation of the Error Term

In order to evaluate if a request can be accepted or not, one has to compare its utility against the utility of the none-option (Equation 3.2). This is achieved by calculating the observable deterministic part of utility (V) of the request with the part-worth utilities obtained by evaluating the DCE (Figure 3.5, step 1). If this value V plus the error term is greater than the utility of the none-option (β_{None}), the request is accepted, as random utility theory states that always the option with the highest utility is chosen.

The evaluation of the DCE is based on the Multinomial Logit model (MNL), which states that when these two utility values are exponentiated, the ratio of the resulting values corresponds to the probability that the request can be accepted (Figure 3.5, step 2).

Our model should comply with random utility theory, therefore the utility functions must have the form of $U = V + \epsilon$. The option with the highest utility is selected and thus a request is accepted if:

$$V + \epsilon \geq \beta_{None} \quad \text{or} \quad \epsilon \leq V - \beta_{None} \quad (3.3)$$

Therefore it is possible to select the standard deviation of ϵ in such a way that the resulting probability distribution leads to an equal choice probability as the one obtained in the MNL model (Figure 3.5, step 3).

However, the distribution of ϵ calculated in this way only accounts for the uncertainty in the MNL model. According to random utility theory, the error term ϵ also accounts for unobserved product attributes or characteristics of the deciding individual (Manski, 1977). Therefore it might be possible that the standard deviation σ of the error term needs to be higher than calculated above. This can be solved by increasing the standard deviation for each agent individually with a factor that is based on the accuracy of the subject's answers. However, since the error term is not measurable, we cannot know its exact probability distribution. The general influence of the magnitude of σ on the model is discussed in the results section.

1. Calculate observable utility

	<u>available</u>	<u>demand</u>	<u>trust</u>	<u>margin</u>	<u>price trend</u>	<u>None</u>
part-worth utilities (β_i)	1.11	3.72	2.30	0.14	-0.50	-0.17
exemplary request (x_i)	10%	3%	40%	CHF 1.40	10%	
Observable utility $V = \sum(\beta_i * x_i)$						1.29

2. Calculate choice probabilities

		<u>probability</u>
exp(V):	3.63	81.1%
exp(None):	0.84	18.9%
sum	4.47	

3. Calculate std. deviation (σ) of error term (ϵ)

$\Delta V = V - \beta_{None}$	1.46
z, where $p(Z > z) = 81.1\%$ (from standard normal table)	-0.88
$\rightarrow \sigma = \Delta V / \text{abs}(Z)$	1.66

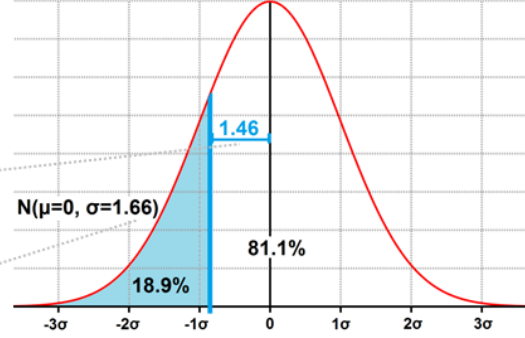


Figure 3.5: Example of the calculation of the standard deviation σ of the error term ϵ to obtain a probability distribution that accounts for the uncertainty in the MNL model. The resulting σ is specific to the given agent for the given request.

3.4.5 Enhancing ABMs with DCEs

Our goal is to enhance ABMs with DCEs by improving the empirical foundation of the model and benefitting from the well-established random utility theory. Empirical information can be used either as input data or to test a model (Janssen and Ostrom, 2006). Our approach uses the DCE data as input data for the decision model of each forester agent.

As (empirical) validity is not measurable, but rather a subjective human judgment (Amblard et al., 2007), it is difficult to quantify to what extent the ABM is enhanced by the empirical data and thus to assess the success of our approach. Additionally, the extent to which the ABM is enhanced would depend on the accuracy of the estimated decision behavior without having empirical data from the DCE. Hilty et al. (2014) describe this as the problem of defining the baseline. We therefore assess our approach by performing a parameter variability-sensitivity analysis (Sargent, 2005). With this validation method, we check the plausibility of the simulation output when agents are parameterized with the results from the DCE. We focus on control variables of which their evolution in reality and under normal market conditions is known. By using the validation methods described in the section "Observation", we ensure that these observed variables always stay within a realistic range over the entire simulation period. This is, the behavior of the market participants in our simulation is compared with the

expected behavior in reality. To illustrate this process, we identified one variable as a fitness measure. This variable is explained in the following section.

The reasons explained above prevent a real proof that our approach does in fact enhance ABMs; however, we are convinced that including empirical data in a model is in most cases an improvement of a model. By including empirical data on the micro level we also aim at a higher structural validity (cf. Zeigler et al., 2000) of the model, as we try to generate the macro behavior with a similar mechanism as in the real system. It may be possible that a model with "invented" (non-empirical) decision parameters would perform better regarding the model validity on the macro-level, but this would prevent from understanding the causal mechanisms inside the ABM. This is discussed in detail by Boero and Squazzoni (2005), where they state (2.13): "[...] what else, if not empirical data and knowledge about the micro level, is indispensable to understand which causal mechanism is behind the phenomenon of interest?".

3.4.5.1 Observed Fitness Variable

In our study region (cf. section "Experimental Setup"), foresters try to equate yearly wood sales to the level of yearly wood growth, as long as no storm damages occur. This means that the amount of wood sold annually per forester can be assumed to be nearly constant, as it depends mainly on the size of the forest. We define our fitness variable as the ratio of roundwood sold in one year to the amount of wood that is regrown in the same period and usable as roundwood. Harvesting more wood in one year than the amount that regrows is not allowed, which is regulated by the determination of the annual allowable cut. Therefore the defined fitness variable should always have a value very close to one, but not greater.

Because we know which value this variable should normally have, it is ideally suited for checking the plausibility of the DCE results. In our DCE, the foresters had to imagine themselves being involved in the presented situation and decide how they would react in it. Therefore, the 12 decision situations presented to each subject only represent 12 arbitrary situations in a year. A problem of such stated preference methods is the possibility that a subject indicates decision behavior that does not conform to reality. In our case, this would mean that if we equip each forester agent with the indicated decision behavior obtained from the DCE, it could lead to too few or too many transactions in the model. This would imply that the decision behavior parameters are not plausible

3.4.6 Simulation Procedure

The current version of the simulation program is intended to verify the suitability of using DCEs to parameterize an ABM and to evaluate different approaches to integrating the DCE data. Therefore only a standard market situation without any special market events (e.g., entry of new market participants) is simulated. In the simulated market situation, the margins of the foresters are rather low, but still within the range that

was covered by the DCE. This procedure is necessary because if the margins were very high, the foresters would almost always sell, and there would be little to observe.

In each simulation run, a period of 20 years is simulated. The first three years of the simulation are ignored in the analysis to avoid bias due to the initialization phase (cf. Figure 3.3). Because the model is stochastic, each simulation run is repeated 100 times using different random seeds.

3.5 Results and Discussion

3.5.1 Comparison of Hierarchical Bayes and Latent Class Analysis

Latent class analysis (LCA) can divide a sample into an arbitrary number of classes; for simplicity's sake, we used an example with three and later one with two classes. To illustrate the consequences of using either hierarchical Bayes (HB) or LCA to parameterize the decision behavior of the agents, a comparison of the two approaches is presented in Figure 3.6. In order to check the plausibility of the decision behavior parameters, we observe the fitness variable defined above, which should always have a value very close to one. The error term is set to zero in this example permitting a better comparison of the results.

Each approach has its specific advantages and disadvantages. Since HB estimates an individual utility function for each DCE respondent, it is very sensitive to the answers the respondents give. This also implies that respondents who do not respond with reasonable care (reasons may be, e.g., reluctance or fatigue) provoke utility functions and therefore decision behavior parameters that make it impossible to survive on the market. One such possible case occurs if a forester agent never sells, although he should. This can be observed in the left diagram of Figure 3.6; there are three forester agents who sell less than half of the available roundwood, and one who does not sell anything at all. This leads to an average of the observed variable of around 93%. It should be noted that the first three years of the simulation are omitted from the calculation of the averages, cf. section "Simulation Procedure".

The right diagram in Figure 3.6 shows the simulation results when the agents are initialized with LCA parameters using three classes of agents. The overall average is slightly higher with 97%. However, if per-class averages are examined, a similar phenomenon can be observed. There are two classes with an observed value of about 99%, and one class with an average value of about 82%. The latter class contains nine of the 80 foresters modeled.

Whether HB or LCA is the more appropriate approach firstly depends on the quality of the DCE survey data and secondly on the scenarios to be simulated. Low data quality, for example caused by subjects reluctantly participating in the DCE, might lead to implausible results when using HB. This effect might be reduced by manually sorting out the data of some respondents. However, this poses a risk for a selection bias, and it might be difficult to differentiate between low data quality and unusual but existing decision behavior. LCA is more robust to such outliers, but also reduces

the diversity of decision behaviors. Whereby it is this diversity in which each market participant can be modeled with an individual way of deciding that is one of the key benefits that agent-based simulations provide.

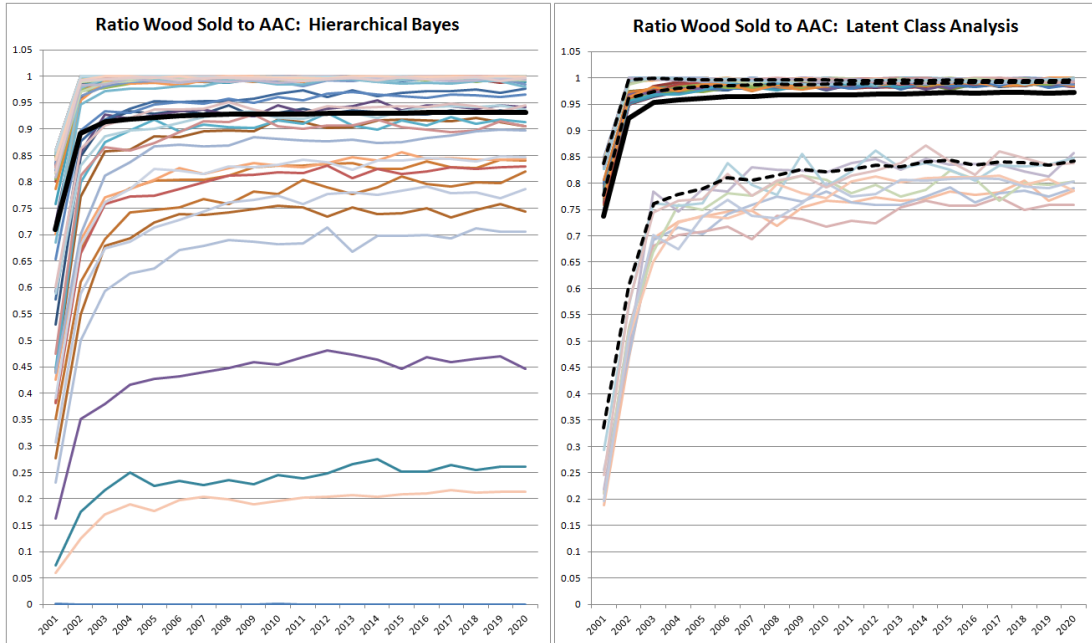


Figure 3.6: Comparison of HB and LCA for a simulation period of 20 years. The variable shown specifies the ratio between the amount of roundwood that has been sold and the annual allowable cut of roundwood. Each colored line represents one of the 80 simulated forester agents, while the black line represents the average. The three dashed lines in the right diagram represent the averages of the three different classes identified by latent class analysis.

3.5.1.1 A Closer Look at Latent Class Analysis

Figure 3.7 shows the per-class average price foresters receive for roundwood when they are divided into two classes using LCA. Two interesting phenomena can be observed. First, the class that gives more weight to the margin criterion (class 1) also achieves higher prices. Second, in class 1 the prices rise towards the end of the forest year, while in the class 2 they fall. This can be explained by looking at the coefficients for the criterion "amount of wood available": class 1 has a positive coefficient, while class 2 has a negative one. A positive coefficient means that a forester is more likely to sell wood whilst still having a large amount of available wood, i.e., at the beginning of the forest year. Therefore, there is a tendency to negotiate higher prices towards the end of the year. The class with the negative coefficient behaves conversely. Note that the average simulated market price after several rounds is largely independent on the initial price level given at the start of the simulation. As we simulate a business-as-usual scenario

without external influences such as import/export or scenarios of over- or undersupply, the price solely emerges from the utility functions of the agents.

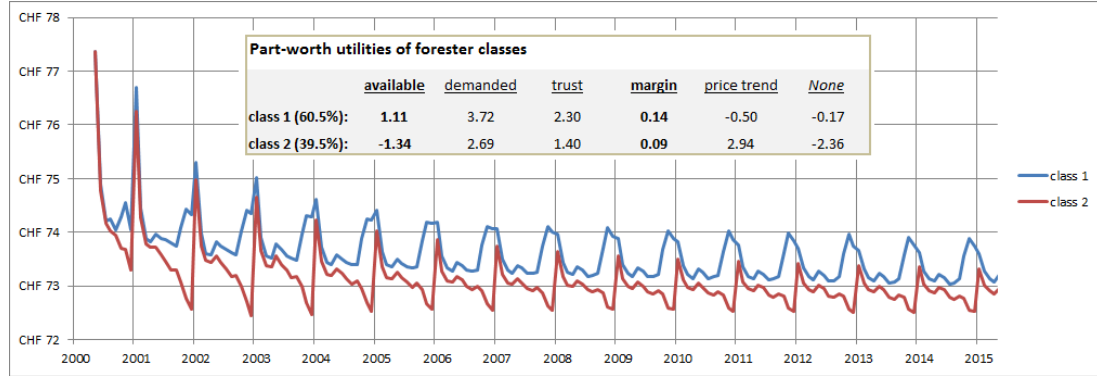


Figure 3.7: Comparison of average roundwood prices in two different classes of foresters.

With LCA, the subjects in the sample can be divided into an arbitrary number of classes. The model builder must choose the appropriate number of classes. When consulting experts operating in the Swiss wood market with the two- and three-class parameter set, they clearly favored the two-class approach. They could not imagine that there are foresters that rate all attributes more or less the same, as a class with about 10% of the subjects indicated in the three-class approach. The simulation which applied three classes confirmed their expectation that the behavior of the agents in this 10% class is rather implausible. Because such an effect can only be verified in a simulation, simulating results obtained by DCEs also increases the transparency of these results. However, an explanation for such behavior, while seemingly implausible, might be that product attributes that are important in the decision of an individual were not included in the DCE. This shows the importance of the error term of the utility function, which accounts for such cases.

3.5.2 Influence of the Error Term

Figure 3.8 illustrates how the magnitude of the error term ϵ influences the simulation results. The standard deviation of the error term is set in relation to the average ΔV (see Figure 3.5) and is varied between 40% and 400% of the average ΔV . The observed variable is again the fitness variable described above, the ratio between roundwood sold and the annual allowable cut, which should always be close to one. It can be observed that the variance of the curves decreases with an increasing standard deviation of the error term. The reason for this effect is in the error term whereby increasing its standard deviation respectively increases the randomization of the entire utility function. This means that utility functions which previously resulted in very low market activity now have a higher probability of allowing normal market participation. However, this leads to the effect that more negotiation rounds are necessary when the standard deviation increases. The additional negotiation rounds compensate for the increased randomness in the utility function; if the randomness is high, the probability that lucrative offers are rejected and unprofitable ones accepted increases. Therefore, a high standard deviation

of the error term also leads to lower cost-effectiveness of the market. However, including the error term in the utility functions is important, as otherwise they are no longer consistent with random utility theory (cf. section "Discrete Choice Experiments" / Louviere et al. (2010)).

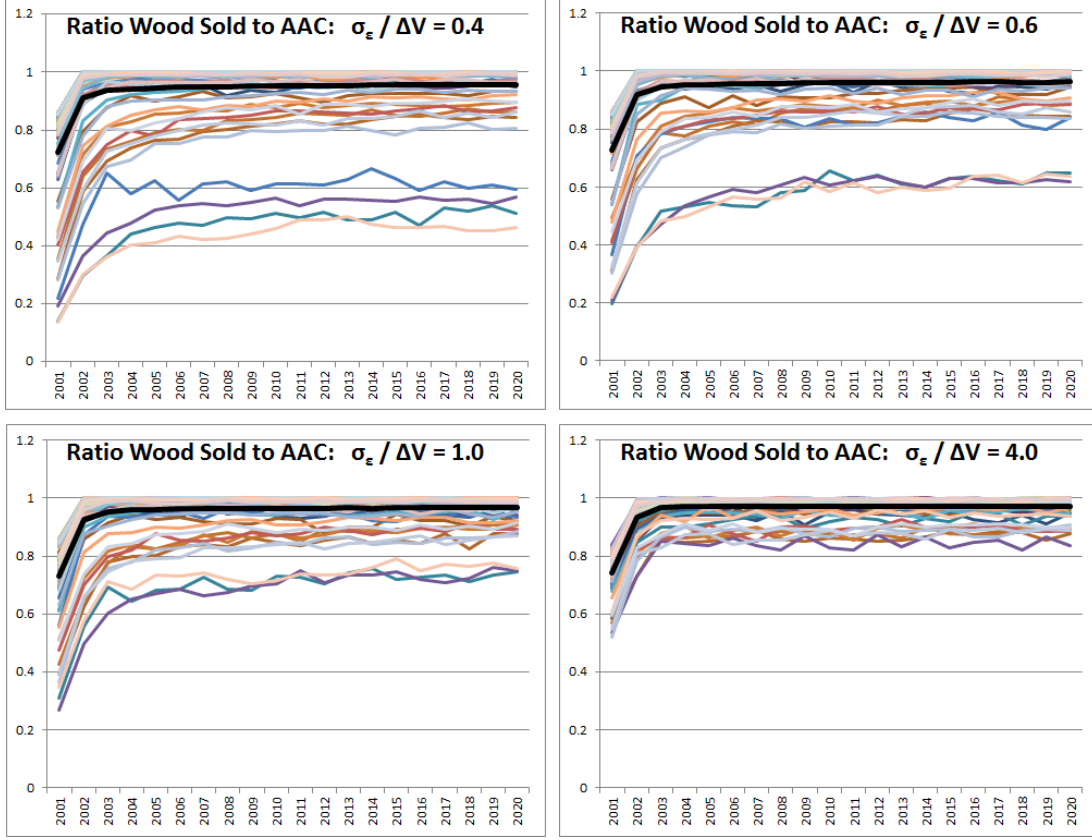


Figure 3.8: Influence of the standard deviation σ of the error term ϵ on the simulation result with utility functions based on hierarchical Bayes. The selected ratios of $\sigma/\Delta V$ correspond to choice probabilities of 99.4%, 95.2%, 84.1%, and 59.9% for the option with the highest V (cf. Figure 3.5). The development of the same variable with $\sigma = 0$ can be seen in Figure 3.6.

3.5.3 Challenges of the Approach

Several challenges emerge when using DCEs to parameterize an ABM. The first challenge is data collection. The number of attributes and levels in the DCE must be in accordance with the number of subjects in the survey, the sample size. A rule of thumb for DCEs with aggregated analysis is defined by Johnson and Orme (2003) and Orme (2009). They recommend calculating the minimum sample size with Equation 3.4,

$$n \geq (500 * c) / (t * a) \quad (3.4)$$

where n is the number of respondents, t the number of tasks, a the number of alternatives per task (without the none-option), and c the number of levels per attribute when only main effects are considered. For our experimental setup, this would require at least 63 respondents.

A more general statement was made by Lancsar and Louviere (2008): "one rarely requires more than 20 respondents per version to estimate reliable models". We were able to conduct almost a full population survey ($n=55$, $N=\text{ca. } 80$), though the absolute number of subjects was still not very high. The problem was also exacerbated in that some respondents felt the survey method overly theoretical, which may have reduced the data quality. However, we suppose that a population data coverage of 70% is sufficient for the given purpose.

Another problem is "how to derive observations of a social system over time" (Janssen and Ostrom, 2006) or, in other words, "using cross-sectional data to estimate parameters of function forms of agents' decisions" (Villamor et al., 2012). This problem also occurs when conducting DCEs. Even when multiple hypothetical decision situations are presented to each subject; we might face the problem that the subject has the current market situation in mind, which might influence his decision. It is therefore possible that we would obtain different data if the real market situation changed. If it is not possible to repeat the experiment at different points in time, this problem could be reduced by considering in the DCE more attributes per option that also take the market situation into account. However, adding more attributes complicates data collection, because more respondents or more questions per respondent are necessary.

Finally, we only collected data from the selling side of the market, which directly influences the interaction with the forester agents. This is the case because forester agents might be faced with nonsensical requests or offers from sawmill agents that can for instance lead to an unrealistic shift of market power. This can only be avoided by estimating and calibrating the sawmills' decision behavior parameters with reasonable care.

One way to address some of the problems mentioned could be to automatically adapt the utility function of each agent during simulation. This could be achieved through learning algorithms that adapt the utility functions in small steps to the changed simulated market conditions. However, this would weaken the empirical foundation on which the original DCE was created.

3.6 Conclusion and Outlook

We presented an approach combining DCEs with ABMs and conclude that DCEs are a suitable method to enhance the empirical foundation of ABMs. We demonstrated this approach within a case study of a Swiss roundwood market. By observing a fitness variable, we were able to state that the decision behavior parameters of the agents obtained through the DCE are plausible for most agents. For the small share of seemingly unusual decision behavior, the standard deviation of the error term can be increased, which is in accordance with random utility theory. We presented a method to

calculate this standard deviation and demonstrated how increasing it leads to increased randomness of decisions and hence lower cost-effectiveness of the market.

The comparison of latent class analysis (LCA) and hierarchical Bayes (HB) as DCEs evaluation methods prove in both cases to be useful for evaluating DCEs and integrating the results into an ABM. While LCA is more robust to outliers (which may originate from low data quality), HB is better suited to the agent paradigm as each individual agent can have his own empirically based decision behavior.

As the approach of enhancing ABMs with DCEs looks promising for our application, our next step will be to conduct the DCE with the buying side of the wood market. Our goal is to implement a model of the Swiss wood market containing all three major wood assortments and corresponding agent types (cf. Figure 3.1). This will enable us to simulate scenarios that can provide decision support for policy-makers and other interested parties.

3.7 Acknowledgements

This work is part of the project "An economic analysis of Swiss wood markets", which is funded by the Swiss National Science Foundation through its National Research Program "Resource Wood" (NRP 66).

3.A Appendix

3.A.1 UML Class Diagram

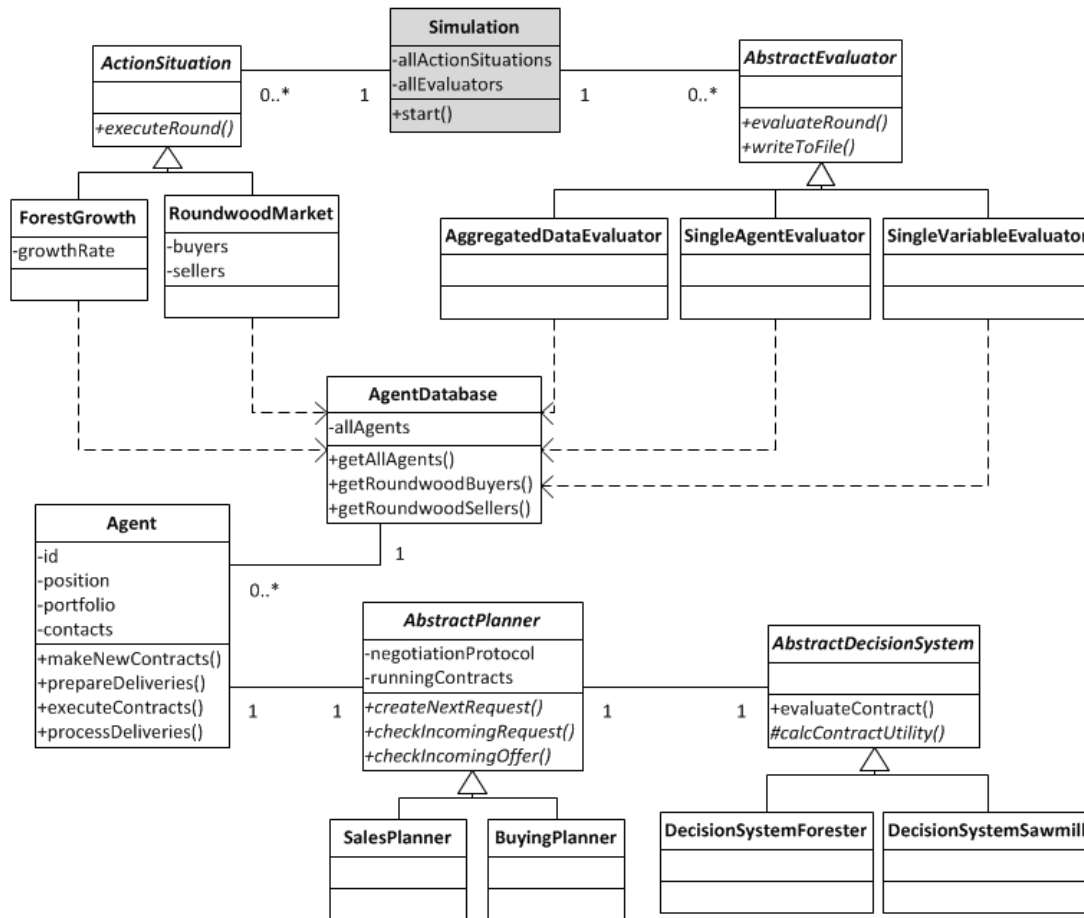


Figure 3.9: UML diagram showing the most relevant classes of the simulation program. In each simulation round, first all action situations are executed, then multiple evaluator classes evaluate the new status of the simulation. Each agent has a planner that supports him in negotiating new contracts to have continuous supply / sales.

3.A.2 Pseudocode

```
Simulation.start() {
  FOR EACH round {
    forestGrowth.executeRound()
    roundwoodMarket.executeRound() //details see below
    FOR EACH evaluator {
      evaluator.evaluateRound()
      evaluator.writeToFile()
    }
  }
}
```

Table 3.2: Pseudocode of the main method.

```
RoundwoodMarket.executeRound() {
  allAgents.shuffle()
  FOR EACH agent {
    // Conclude new contracts with the
    // subgoals mentioned in section "Individual Decision-Making"
    agent.makeNewContracts()
  }
  FOR EACH seller {
    seller.prepareDeliveries() //foresters harvest wood
    seller.executeContracts() //wood is transferred from buyer to seller
  }
  FOR EACH agent {
    buyer.processDeliveries() //sawmills process the wood received
  }
}
```

Table 3.3: Pseudocode of the roundwood market execution method.

3.A.3 DCE data

Percentage	Available	Demanded	Trust	Margin	Price Trend	None
0.521	1.10765	3.71545	2.29954	0.13907	-0.50003	-0.17317
0.365	-1.33519	2.69343	1.39942	0.08656	2.93641	-2.36081
0.114	-2.76458	7.73036	2.43698	0.06526	15.15206	-0.26193

Table 3.4: DCE data used for the latent class analysis example.

Respondent ID	Available	Demanded	Trust	Margin	Price Trend	None
1	-1.65021	11.74185	1.48699	0.15045	27.9498	-0.32893
2	0.00152	2.7108	5.86578	0.09515	-4.68225	-0.34429
3	-0.93907	5.69982	5.73421	0.17154	9.39712	-1.73636
4	-0.20594	2.33914	6.60405	0.23196	-10.79376	0.31855
5	0.48267	5.1465	1.14684	0.01039	4.58829	-1.69116
6	-0.05803	5.31644	3.92213	0.20255	-2.34701	1.46233
7	3.53005	4.62726	0.43271	0.08359	9.86007	-0.74989
8	1.03595	1.81	1.26642	0.01212	-6.1483	-4.34665
9	1.29175	3.2495	3.28484	0.22383	2.36744	-3.70485
10	-0.72595	5.86004	1.67825	0.26147	6.32396	-4.58434
11	-3.7714	12.07729	1.70283	-0.03799	25.765	-2.91517
12	-0.64134	8.66919	0.58588	0.85216	15.23726	-2.73378
13	-2.38885	9.75864	2.67844	0.24657	19.48115	-3.76842
14	1.47113	1.94409	5.63944	0.15977	-8.73772	0.94164
15	0.44531	5.3594	3.3253	0.19398	0.54057	-0.40329
16	0.68513	6.56316	0.70069	0.1629	4.2541	0.09896
17	-0.69656	6.18657	4.20723	0.34206	-0.80857	3.16604
18	1.11296	6.6634	3.31843	0.84481	8.06414	-0.74866
19	0.43058	8.34134	1.61603	0.24749	10.11763	-0.26094
20	0.52809	3.32461	3.3177	0.18038	-8.54455	-1.11341
21	1.03296	4.5115	4.35263	0.05935	6.28141	-0.5846
22	-2.57125	10.19657	0.41028	0.00238	9.9161	-2.34199
23	-1.96979	2.11568	2.3026	0.0533	-20.95443	-1.47928
24	2.65001	3.70051	1.57828	0.84137	8.09823	-2.12457
25	-0.01849	6.02466	2.32619	0.11939	-1.67464	-0.15444
26	-0.71414	4.73313	4.6687	0.23562	-5.16314	-0.9748
27	-0.90609	5.99437	4.26545	0.03039	7.9698	0.26158
28	2.24163	3.11603	2.7478	0.21428	-1.59987	-2.08913
29	-0.80157	5.809	2.49672	0.30295	8.62159	-3.36045
30	-1.78717	8.37476	4.15142	0.11689	15.34745	-1.11911
31	2.60449	-0.18525	2.17123	0.13614	-10.09713	-0.3845
32	-0.88535	5.57735	3.11717	0.10382	4.42179	-2.89004
33	1.25579	5.57075	2.49091	0.16504	4.07795	-0.52886
34	0.5901	3.62148	3.9655	0.79139	-8.39507	1.37867
35	-2.45724	9.34384	2.73292	0.29417	16.68159	-3.43844
36	0.10763	5.43047	3.14805	0.23269	-0.64867	-1.32549
37	-2.24524	10.24467	1.1318	0.09598	9.4068	0.99438
38	-0.30457	9.82876	-0.06199	0.056	20.60886	-0.59821
39	0.9982	6.18441	0.79915	0.25892	10.17568	-2.38179
40	0.58834	3.92607	3.35001	0.07797	2.16074	-4.57116
41	-1.66035	3.96522	3.93209	-0.00443	-1.15795	-3.02296
42	-1.97189	7.22988	1.38998	0.1213	11.93619	-5.62056
43	0.82819	4.7467	0.9625	0.22142	3.96102	-0.63942
44	1.54494	6.12931	3.13649	0.82428	8.72477	-1.06492
45	1.95801	4.49723	2.90722	0.08472	7.18297	0.98367
46	1.04304	4.29444	1.97797	0.29028	5.68395	-4.11341
47	-2.3322	10.35659	2.32305	0.42228	18.24946	-2.65153
48	-0.97862	6.06758	4.7696	0.22328	0.21119	-0.12754
49	0.6094	4.66721	0.57257	0.12686	-6.20349	-0.75471
50	-2.8735	7.12722	3.65683	0.06123	7.4203	-3.33714
51	0.51633	7.26817	2.54608	0.12281	7.2992	-2.4483
52	0.54491	3.98197	3.23532	0.19742	2.13933	-4.80881
53	-2.37632	10.46205	-1.59661	0.20672	15.16371	-3.85899
54	2.29437	0.31326	4.51728	0.35852	-15.97996	2.14107
55	-0.66437	8.80765	2.02634	0.13916	22.59912	-4.28693

Table 3.5: DCE data used for the hierarchical Bayes example.

Empirical validation of an agent-based model of wood markets in Switzerland

Holm, S., Hilty, L.M., Lemm, R., & Thees, O. (2018). Empirical validation of an agent-based model of wood markets in Switzerland. *PLoS ONE*, 13(1):e0190605. doi:10.1371/journal.pone.0190605

Abstract

We present an agent-based model of wood markets and show our efforts to validate this model using empirical data from different sources, including interviews, workshops, experiments, and official statistics. Own surveys closed gaps where data was not available. Our approach to model validation used a variety of techniques, including the replication of historical production amounts, prices, and survey results, as well as a historical case study of a large sawmill entering the market and becoming insolvent only a few years later. Validating the model using this case provided additional insights, showing how the model can be used to simulate scenarios of resource availability and resource allocation. We conclude that the outcome of the rigorous validation qualifies the model to simulate scenarios concerning resource availability and allocation in our study region.

4.1 Introduction

Agent-based Modeling (ABM) is a bottom-up modeling approach, where "a system is modeled as a collection of autonomous decision-making entities called agents" (Bonabeau, 2002). This requires that the system under study can be decomposed into its constituent units. ABM is especially beneficial if such decomposition and the description of the resulting units leads to a natural representation of the system (Bonabeau, 2002; Macal and North, 2014). Important advantages of using ABM are the possibilities of modeling each agent individually and capturing emergent behavior at any level of aggregation (Bonabeau, 2002; Macal and North, 2014).

While the reasons for modeling and simulation are manifold (Epstein, 2008), Kelly et al. (2013) identified two model purposes for which ABM is the most appropriate approach, namely system understanding and social learning. While prediction is often

assumed to be the main purpose of modeling and simulation (Epstein, 2008), this is in fact seldom the case for agent-based models: Heath et al. (2009) analyzed studies that used ABM and were published between 1998 and 2008, and did not find a single study that uses an agent-based model for prediction as the main purpose. However, there are different notions of the term "prediction". Heath et al. (2009) state that if a model is used as a predictor, "it is used like a calculator to provide clear and concise predictions about the system", in contrast to its use as a mediator, when there is less understanding about the real system and "the simulation provides insight into the system, but is not a complete representation of how that system actually behaves". Kelly et al. (2013) differentiate between prediction and forecast, where prediction leads to "if-then" results (exogenous factors of the model are known or assumed), and forecast, where statements regarding the future are made without knowledge of the exogenous factors of the system (everything is calculated inside the model). The differences between prediction and forecast are field-specific, as can be seen in the example of seismology, where "A prediction is a definitive and specific statement about when and where an earthquake will strike [...] Whereas a forecast is a probabilistic statement, usually over a longer timescale" (Silver, 2012). In this article, we use the term "prediction" according to the definition of Kelly et al. (2013), whereas, according to Heath et al. (2009), our model would be a "mediator".

ABM has been used in a multitude of disciplines, such as social sciences, economics, biology, traffic simulation, and crime analysis (Macal and North, 2014; Heath et al., 2009; Macal, 2016). While early agent-based models were rather theoretical and abstract (Janssen and Ostrom, 2006), e.g., Schelling's segregation model (Schelling, 1971), or Axelrod's modeling of different strategies in the Prisoner's Dilemma (Axelrod, 1980), large and complex systems are modeled and simulated today to draw conclusions for, e.g., policy making (Macal, 2016; Jager and Edmonds, 2015). This makes model validation and the integration of empirical data into an agent-based model important. Empirical data can be used as input data for the model (to specify and calibrate the model at the micro level) and to test it (validate the simulation results at the macro level) (Janssen and Ostrom, 2006; Boero and Squazzoni, 2005). In our case, empirical data was used for both purposes, i.e., to specify and validate the model. In a survey by Heath et al. (2009), they found that the majority of agent-based models is not validated both conceptually and operationally, which they deemed unacceptable. However, they also revealed that, over the 10-year evaluation period, there is a clear trend towards more validation efforts. More recent literature (Macal, 2016; van Vliet et al., 2016) indicates that the situation has only been changing slowly since 2009.

In this paper, we present an agent-based model for which empirical data was collected from several sources and divided into two sets: data for model development and data for model validation. The model is intended to represent the wood markets in Switzerland. These markets have several peculiarities which qualify ABM as an appropriate modeling method. It was created to facilitate a better understanding of these markets by simulating scenarios focused on wood availability and allocation. An initial version of this model was presented in Kostadinov et al. (2014), in which three main opportunities were identified to improve the model, namely the gathering of empirical data for the decision-making process of the agents, a more realistic modeling of wood transport routes (which affects transportation costs), and a better handling of

the model boundaries (avoiding boundary effects). These issues are addressed in the present article. The model has been substantially redesigned and re-implemented to be more realistic with regard to these issues, while also improving the software architecture to reduce the model's execution time. The approach is demonstrated with an ex-post case study on the market entry of a bulk purchaser.

The following section gives an overview of the model, the methods applied, and the empirical base of the model. In section 4.3, results are presented and discussed. Section 4.4 concludes the article.

4.2 Materials and methods

In this section, first, a condensed description of the model is presented. Then, an overview of the applied calibration and validation methods is given. Finally, the empirical data used to calibrate and validate the model are described, including official statistics, data from our own surveys, and the historical event of a bulk purchaser entering the market in 2007 and becoming insolvent in 2010.

4.2.1 Description of the model

The following model description is based on the structure of the first sections of the ODD+D protocol (Müller et al., 2013), an extension of the ODD protocol (Grimm et al., 2006, 2010). The aim of ODD+D is to provide a better understanding of how human decision-making is modeled. This description should provide the reader with a basic understanding of the model, which is necessary to understand the subsequent chapters. An earlier version of the model is described in Holm et al. (Holm et al., 2016); thus, parts of the model description may overlap.

4.2.1.1 Purpose

The overarching goal of this study is to show ways how additional amounts of different wood assortments can be made available to consumers, as the sustainable potential of wood as a resource is currently not reached in the study region (the canton of Grisons (GR) in Switzerland), i.e., the annual growth of wood is larger than the annual amount harvested. The model was developed to provide insights into the processes of resource allocation in the modeled markets. It should help to identify the conditions under which resource availability can be increased, with a focus on the decision behavior of the agents and structural parameters, such as the presence of intermediaries.

The current version of the model is designed to be used by the authors to simulate scenarios on behalf of stakeholders. A direct operation of the model by the stakeholders is not intended owing to the complexity of the model.

4.2.1.2 Entities, state variables, and scales

The model consists of the following overlapping markets: the markets for sawlogs, which are the main product, and the markets for two side-products, namely industrial wood and energy wood. For each product, there is one market for softwood and another for hardwood, resulting in six markets in total. There are producing agents, intermediaries, and consumers for each of the products (see Fig 4.1). A typical model run simulates a 20-year period, where a single time-step represents one month.

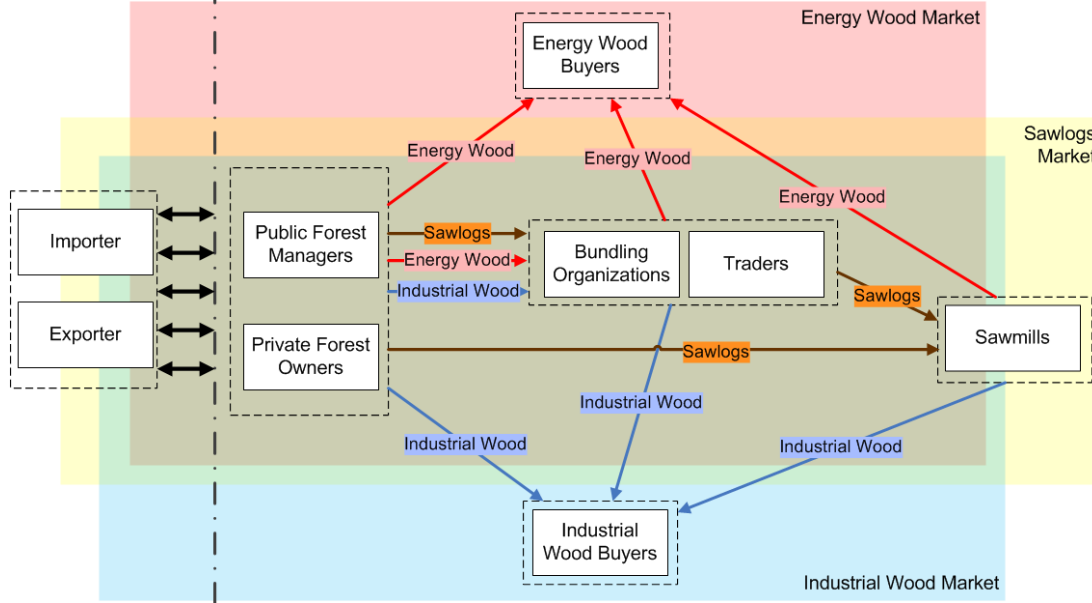


Figure 4.1: Conceptual model: agents and markets.

As the model represents an existing geographical region, it is necessary to handle boundary effects (sometimes called border effects), which is a challenge in many spatial agent-based models. If artificial regions are used, such effects are often avoided by applying a torus ("doughnut") structure (e.g. Laurie and Jaggi (2003); Segovia-Juarez et al. (2004); Evers et al. (2011)). However, in this case, the modeled region is real and highly dependent on adjacent areas, especially concerning the prices of wood, which depend on the global market prices; these are exogenous factors in the model. On its eastern side, the study region borders on other countries (with a different currency), whereas the western side of the study region borders on domestic regions. Therefore, we have two kinds of borders, which need to be handled differently. Where the study region borders on other countries, importer and exporter agents are distributed along the border to sell or buy wood at prices based on historical price data from adjacent countries, and the corresponding exchange rate. Where the study region borders on domestic regions, an additional belt of agents is modeled. These represent the part of the domestic market with a direct influence on the study region. We call this belt the outer zone of the model, while the study region itself is called the inner zone of the model. The agent quantities, properties, and their behavior are similar in both zones. The outer zone acts as a buffer zone to avoid boundary effects in the inner zone. This allows the evaluation of variables such as transportation distances in the inner zone.

Consequently, the validation focused on the individual and the aggregate behavior of the agents in the inner zone. However, necessary parameter changes identified during calibration and validation were always applied for the agents in both the inner and the outer zone. For the evaluation of simulation results, only the agents in the inner zone are considered (Fig 4.2). With this approach, we managed to overcome the boundary problems we were facing in a previous study (Kostadinov et al., 2014), which was one of the main issues identified therein.

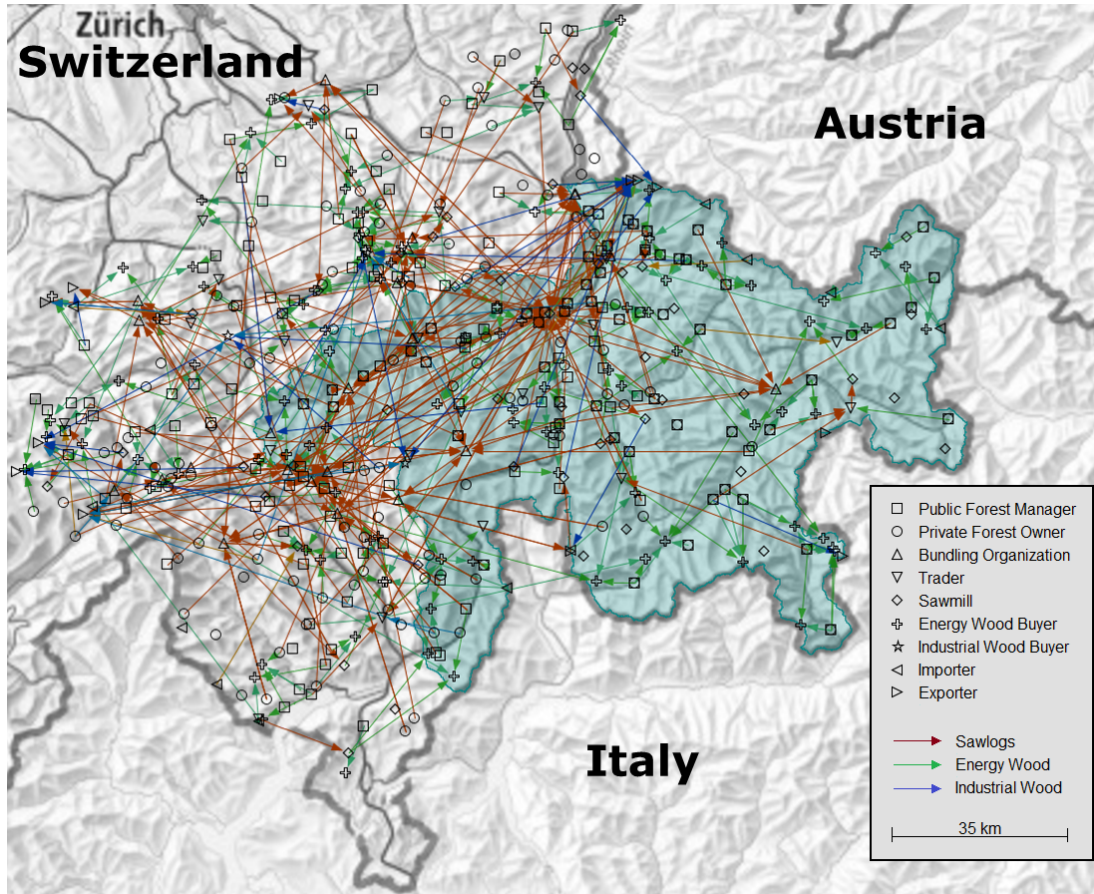


Figure 4.2: **Map showing trading relations at one point in time.** The colored area represents the study region (inner zone); nodes and arrows represent agents and deliveries, respectively.

Each agent has a fixed geographical position on the map that is assigned at the beginning of the simulation run. For public forest managers, this position corresponds to the real-world position of the agent in our study region. The positions of the other agent types are assigned randomly. The agent quantities are listed in Table 4.1. They reflect the actual number of market participants in the study region, unless they are marked as "aggregated", which means that a single agent represents multiple real-world market participants. The following agent types exist in the model:

- **Public forest managers:** These agents manage the public forests in their area. In our study region, 88% of the forest is under public ownership (BFS, 2015a),

which makes them the most important agent group on the supply side of the markets. They sell wood of all six assortments.

- **Private forest owners:** In our study region, 8% of the forest is under private ownership (BFS, 2015a) (the remaining 3.5% of the forest in the study region is hybrid property). In absolute numbers, there are 10'110 private forest owners in the study region that own a total forest area of 16'517 ha (BFS, 2015a). With an average size of 1.65 ha per private forest owner, the wood is usually not harvested by the owners themselves, but with the help of public forest managers or contractors. They are often mentored by a public forest manager. In the model, these agents are aggregated so that there is only one private forest owner agent in the territory of each public forest manager, representing (for model simplicity) the aggregate of all private owners in this territory. They sell wood of all six assortments.
- **Traders:** Traders buy all of the six wood assortments in the model, and try to sell them on the markets at a profit.
- **Bundling organizations:** These agents are cooperatives of small suppliers (private and public), structured to reduce distribution costs and increase market power. They are modeled as intermediaries that are tightly coupled to the affiliated suppliers.
- **Sawmills:** They buy sawlogs and process them into different wood products (for which the downstream markets are not included in the model). During the processing of sawlogs, residuals (tree bark, woodchips, shavings, and sawdust) are accumulated as byproducts and either used by the sawmill itself or sold on the market as energy wood and industrial wood.
- **Industrial wood buyers:** They buy industrial wood and process it into products such as pulp and paper. Downstream markets are not included in the model.
- **Energy wood buyers:** They buy energy wood, predominantly for heating purposes. This includes all consumers from single-family homes with a fireside, up to district heating distributors. These market participants are modeled as aggregated agents.
- **Importers:** They import wood from the outside to the inside of the modeled region.
- **Exporters:** They export wood from the inside to the outside of the modeled region.

4.2.1.3 Process overview and scheduling

Table 4.2 shows the pseudocode (Müller et al., 2014) of the model's main method. The six markets are executed consecutively, month after month, for a simulation period of 20 years. After the execution of each month, multiple evaluator classes analyze the current simulation state and write it to a file.

Agent type	Number of agents (inner zone + outer zone)	Annual supply and/or demand per agent
Public Forest Managers	85 + 85	<p>Annual maximum supply on average ca. 3500 m³ wood, thereof ca. 97% softwood. Distribution of supply values and geographical position reflect actual values in the study region. Softwood: 81% is provided as sawlogs; 13% as energy wood; 6% as industrial wood.</p> <p>Hardwood: 2% is provided as sawlogs; 95% as energy wood; 3% as industrial wood.</p> <p>These values can change over time, depending on assortment prices.</p>
Private Forest Owners	85 + 85 (aggregated)	<p>Annual maximum supply on average ca. 100 m³ wood, thereof ca. 60% softwood. Distribution of supply values and geographical position reflect actual values in the study region. Softwood: 81% is provided as sawlogs; 15% as energy wood; 4% as industrial wood.</p> <p>Hardwood: 1% is provided as sawlogs; 96% as energy wood; 3% as industrial wood.</p> <p>These values can change over time, depending on assortment prices.</p>
Traders	12 + 12	Variable (try to buy and resell as much as possible)
Bundling Organizations	8 + 15	Variable (try to buy and resell as much as possible, but buy only from affiliated wood suppliers)
Sawmills	25 + 25	All sawmills process softwood, between 800 m ³ and 8000 m ³ (avg. ca. 2300 m ³). Three sawmills each process 180 m ³ hardwood in addition. Market entry or exit is possible.
Industrial Wood Buyers	1 + 2	Fixed demand of industrial wood: 4800 m ³ softwood and 1200 m ³ hardwood
Energy Wood Buyers	50 + 50 (aggregated)	Fixed demand of energy wood: 900 m ³ softwood and 225 m ³ hardwood
Importers	6 + 6	Sold amounts are theoretically unlimited, but annual increase is limited
Exporters	6 + 6	Bought amounts are theoretically unlimited, but annual increase is limited

Table 4.1: Quantity structure of the modeled agents.

```

Simulation.start() {
  FOR EACH month { //20 years are simulated
    FOR EACH market { //six markets
      market.executeRound()
    }
    FOR EACH evaluator { //multiple evaluators monitor the simulation state
      evaluator.evaluateRound()
    }
  }
}

```

Table 4.2: Pseudocode of the main method.

The execution of a single market round (one month) is depicted in Table 4.3. The most important step is the first, in which each agent has the possibility to conclude new contracts, either for the current month or for a forthcoming month. Thereby, the agents consider their current and forthcoming demand for or supply of a product, the stock, and the contracts that have already been concluded. The goal of each agent is to be able to meet the demand continuously; or, in the case of a wood supplier, to harvest and sell the wood equably during the harvesting months. As contracting parties, he prefers agents he already knows from successful transactions in the past.

The core algorithm of interaction describes how two agents negotiate a new contract, and is illustrated in Fig 4.3; it is the same for all agents. The negotiation is initiated by an agent who wants to buy or sell wood from a certain assortment. The agent contacts a potential contract partner by sending him or her a request containing the assortment, amount, price, and delivery date. The contacted agent can either accept the request as-is, adapt the price and/or amount, or decline the request. In the first two cases, it is replied with an offer. The agent who initiated the negotiation then has a final opportunity to either accept or decline the offer (no further modifications of the offer are possible). If the agent accepts the offer, the contract is concluded, and will be executed on the specified delivery date(s). The decisions whether a request or offer should be accepted, adapted, or declined, is explained in the following section.

As opposed to the first version of the model (Kostadinov et al., 2014), an agent does not have the possibility to compare several potential contracts and then choose the best one. When an agent receives a request or an offer from another agent, he decides immediately whether to accept or decline it (or to modify it, in certain cases). This approach was chosen because it reflects the common practice of the given market more realistically than the first approach. However, it implies special requirements in the decision algorithm, which are also explained in the next section.

Each agent has a list (herein, a "phonebook") that contains potential contract partners in the surrounding area, with a trust value assigned to each contact. These trust values increase after successful negotiations and decrease after unsuccessful negotiations. They are an important criterion in the agents' decision model. Among other things, contacts with a higher trust value have a higher chance of being considered when an agent wants to make a new contract.


```

Market.executeRound() {
    allAgents.shuffle()

    //step 1: all market participants try to conclude new contracts
    FOR EACH marketParticipant {
        marketParticipant.makeNewContracts();
    }

    //step 2: sellers prepare the deliveries (e.g. timber harvesting)
    FOR EACH seller {
        seller.prepareDelivery();
    }

    //step 3: sellers deliver
    FOR EACH seller {
        seller.executeContracts();
    }

    //step 4: intermediaries deliver
    FOR EACH intermediary {
        intermediary.executeContracts();
    }

    //step 5: buyers process the deliveries
    FOR EACH buyer {
        buyer.processDelivery();
    }
}

```

Table 4.3: Pseudocode of a market round.

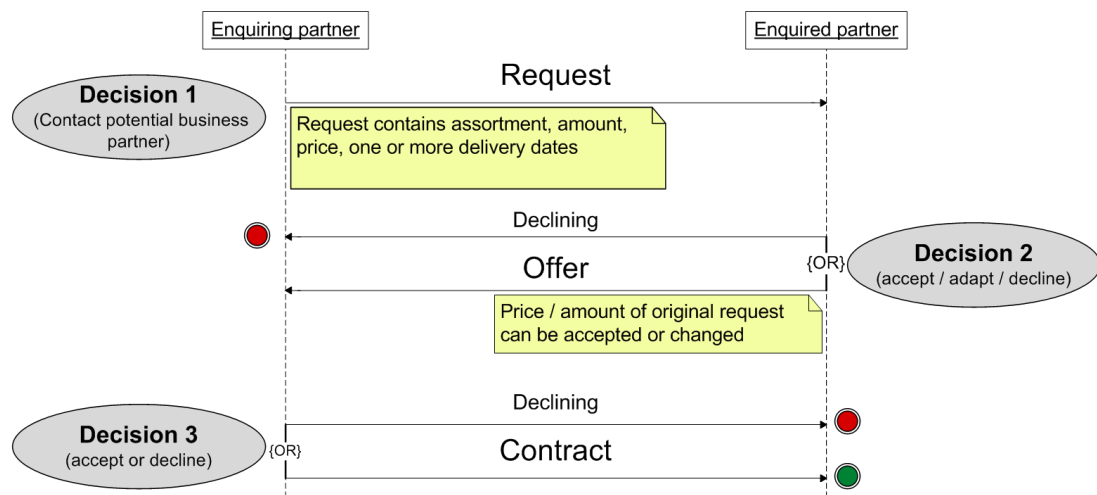


Figure 4.3: **Conceptual model: agent interaction.** This diagram shows how agents conclude new contracts.

4.2.1.4 Theoretical background

As a contract is deliberately not concluded by selecting the best of several options, but by assessing them individually, each agent requires a function to evaluate a single potential contract. We use the following utility function, which is based on random utility theory (McFadden, 1974), to allow our agents to decide whether a request or an offer is acceptable or not; this function is the basis of the agents' decision model:

$$U = \sum_{i=1}^n (\beta_i c_i) + \epsilon - \beta_0 \quad (4.1)$$

where U is the total utility of the request or offer, n is the number of decision criteria an agent considers in a decision situation, β_i is the part-worth utility of criterion i , c_i is the numerical value of criterion i , ϵ is a random component reflecting non-measurable factors in a person's decision, and β_0 is the minimum utility required for a request or offer to be acceptable. A request or offer is accepted if the total utility is greater than zero.

The decision criteria c_i to c_n used by each agent group were defined in interviews and workshops. Then, the part-worth utilities were elicited in discrete choice experiments (DCE), a preference elicitation method widely used in marketing, as well as in other fields of economics. The suitability of using DCEs to parameterize the agents' decision model and the details of this approach are demonstrated in Holm et al. (2016). For the evaluation of the DCEs, we used the Hierarchical Bayes (HB) method, which calculates individual part-worth utilities for each subject, and is, therefore, most suitable for the agent-based paradigm. While the part-worth utilities for the criteria have been taken directly from the DCEs, β_0 requires calibration (as a consequence of the experimental setup, where always three options are compared, which is usually not the case in reality). The random component ϵ is set to zero in the simulations presented here.

4.2.1.5 Individual decision-making

Table 4.4 shows the objectives pursued by the agents and the decision criteria considered during contract negotiation.

4.2.2 Model calibration and validation methods

4.2.2.1 Overview

The goal of validation is to determine if the model is a sufficiently adequate representation of the real system. The validity of a model should be determined with respect to its purpose (Sargent, 2005). The main purpose of our model is to investigate resource availability and resource allocation under conditions defined by the model user. Therefore, the most important variables in the validation process are the provided amounts and prices. There are different concepts of validity (Richiardi et al., 2006); here, we

4.2. MATERIALS AND METHODS

Agent type	Overall objectives	Decision criteria
Public Forest Managers and Private Forest Owners	Harvest the annual targeted amount, distributed as evenly as possible throughout the harvesting seasons, and sell the wood at a profit	Amount available (the annual cut is capped), amount in demand, trust in contract partner, margin (wood price minus harvesting costs)
Bundling Organizations	Bundle goods from the affiliated suppliers and sell at a profit	Sufficient margin
Traders	Buy and sell as much as possible at a profit	Price, trust in contract partner
Sawmills	Constant degree of capacity utilization throughout the year	Buying (sawlogs): urgency, size of order, trust in supplier, price. Selling (by-products): utilized stock capacity, price, trust in buyer
Energy Wood Buyers	Covered demand during heating period	Urgency, price, trust in seller
Industrial Wood Buyers	Covered demand throughout the year	Urgency, price, trust in seller
Importers	Sell at international market price	Price
Exporters	Buy at international market price	Price

Table 4.4: Objectives and decision criteria of the agents.

focus on empirical validity, i.e. the "validity of a model with respect to [empirical] data" (Windrum et al., 2007).

Two basic aspects of a model that need to be validated are the conceptual model (conceptual validity) and the simulation output (operational validity) (Heath et al., 2009; Sargent, 2005). In addition, some authors mention (program) verification as a part of model validation, i.e., measures to ensure that the computer model is a correct implementation of the conceptual model (Sargent, 2005; Page et al., 1991); and, likewise, data validity, i.e., obtaining and using adequate and correct data (Sargent, 2005). Our conceptual model was validated in several workshops with stakeholders during the model-building process, which started by conducting open interviews with real persons corresponding to the model agents, followed by surveys with more specific questions and a larger target group. The simulation output was validated mainly by comparing it to historical observations and data from our own surveys, and also by checking its consistency with expert knowledge. This part of the validation is explained in more detail in subsequent sections. For program verification, standard software testing approaches, such as assertions and unit-tests, were applied. As missing (or low-quality) empirical data is one of the main problems in the validation process (Windrum et al., 2007; Klügl, 2008), we attempted to ensure data validity by conducting our own tailored surveys, which are described in detail in section 4.2.3.2.

A further distinction can be made concerning the type of validity (Zeigler et al., 2000):

- Replicative validity: the model can reproduce known behavior of the real system

- Predictive Validity: the model can predict system behavior that is not yet known.
- Structural validity: the model internally behaves similarly to the real system.

Zeigler specifies these three types of validity as building on each other, with replicative validity at the lowest and structural validity at the highest level. However, in social sciences, there are also models that attempt to be structurally valid without regarding replicative or predictive validity (Troitzsch, 2004); from this point of view, these three types of validity do not necessarily depend on each other. Since our main goal is to understand the processes of resource availability and resource allocation, we aim at replicative and structural validity. For the former, we validated amounts and prices on an aggregated level. For the latter, we looked at variables concerning the individual level, such as behavioral variables and variables characterizing the structure of interaction. These were validated by comparing them to the data gathered in our own surveys. This type of empirical data and knowledge regarding micro-level phenomena is indispensable to understand the causal mechanisms of the processes under study (Boero and Squazzoni, 2005).

Obviously, it is impossible to gather empirical data for all individual micro-level variables in the model; thus, parameterization and calibration were used in addition. According to Railsback and Grimm (2011), parameterization is the process of selecting values for the input parameters of the model. Calibration is a special case of parameterization where values for important parameters are set in such a way that the model reproduces patterns observed in the real system. The purpose of calibration is either to fine-tune known parameters (direct calibration) or to estimate values for parameters with completely unknown values (indirect calibration) (Railsback and Grimm, 2011; Fagiolo et al., 2006). From a formal point of view, calibration is an optimization problem (Klügl, 2008). A third purpose of calibration is to determine whether the model is able to reproduce an expected aggregate behavior by adjusting the input parameters; because, if not, its structure might not be sufficiently realistic (Railsback and Grimm, 2011). As structural validity is one of our requirements, this is an important measure to recognize whether our model needs further improvement or is already sufficiently realistic for the given purpose. The reproduction of patterns observed in the real system is also referred to as "pattern-oriented modeling" (POM), especially in ecology (Wiegand et al., 2003; Grimm et al., 2005). POM aims at improving the structural validity by finding a model structure and model parameters that reproduce multiple patterns simultaneously. The observed patterns preferably occur on different levels of aggregation: in a market model such as the one presented here, a pattern on a high level of aggregation could be traded quantities in a certain region over time, on a lower level of aggregation the typical delivery quantity of a single transaction.

According to the definition of prediction used by Kelly et al. (2013), we also aim at predictive validity in the sense that the model must be able to estimate the system behavior when exogenous model variables are changed, so that their influence on the system behavior can be examined. There is a long-standing controversy regarding whether prediction and explanation are equal (Troitzsch, 2004; Scriven, 1959; Grünbaum, 1962). Some authors also state that "prediction should be the real aim of every model" (Bianchi et al., 2007) or that "validation of social simulation models requires prediction" (Moss, 2000). In contrast, they are seen as different by other au-

thors, such as Epstein (2008), who illustrates the distinction with the example that earthquakes are explainable, but not predictable. As stated in the introduction, we follow the definition of Kelly et al. (2013) in this paper.

4.2.2.2 Validation techniques applied

An overview of validation techniques is given by Sargent (2005). We used the following for the validation of our model:

- **Animation:** A map showing the development of the agents' trading relations over time was observed during simulation (cf. Fig 4.2), as well as the resource flows among agents of different types.
- **Event Validity:** The behavior of the model after a market entry of a very large sawmill agent was compared to such an event that was observed in the real system some years ago (details will be presented in section 4.2.3.3).
- **Face Validity:** The behavior of the model (as well as a presentation of the conceptual model) was discussed with domain experts.
- **Historical Data Validation:** Historical data on amounts and prices were used to validate the model. This will be explained in more detail in section 4.2.3.1.
- **Operational Graphics:** A vast number of variables were observed during simulation at different levels of aggregation: the most important variables were observed at the level of individual agents; others were aggregated over all agents or agents of some type. It was observed, for example, whether all agents were sufficiently supplied, and whether local price differences stayed in a realistic range.
- **Parameter Variability-Sensitivity Analysis:** This was conducted together with the calibration of the model to determine the effect of the input parameters on the simulation results.
- **Traces:** A separate application program was developed to trace individual agents in more detail. For every agent type, a few agents were selected for which a snapshot of each simulation time step was recorded during the simulation. Such a snapshot includes an agent's current stock of all resources and the current status of all negotiations with other agents. These snapshots were then analyzed with this tracing application in a post-processing step. This approach allows to examine in detail which negotiations led to a contract and which not, and reveals the reasons for the underlying decisions. It also shows the activity of an agent, i.e. how many other agents are contacted, and how many negotiations are initiated from other agents. The tracing application thereby not only allows validation from the perspective of single agents; it is a very helpful instrument in all stages of model development, as it also facilitates verification (in particular finding and fixing bugs) and supports the in-depth analysis of emerging phenomena.

Some of these techniques can be realized with statistical tests (e.g. hypothesis testing); others only with non-statistical approaches that involve subjective judgments, e.g., by expert opinion or qualitative comparisons (Heath et al., 2009; Sargent, 2005).

However, in almost all cases related to agent-based modeling, they are applied non-statistically (Heath et al., 2009). We also focused on expert opinion and qualitative comparisons here.

There are two further aspects worth mentioning. The first is the selection of the validation period, i.e., the years over which the empirical data is compared to the simulated data (cf. Windrum et al., 2007). We started in the years between 2001 and 2004 (depending on the variable) for the following reasons: first, there was a hurricane in 1999 which felled trees in the volume of approximately three times the annual cut in Switzerland (WSL/BUWAL, 2001), which had a strong impact on the market. The second reason is the lack of data availability or quality prior to these years. Third, our simulations start in 2001, and the model needs several time-steps to settle down (relationships between agents need to be established etc.); therefore, the initial simulation months cannot be used for validation, as they might be biased.

The second aspect is the determination of when to stop the validation (and, thereby, the related calibration process). As structural validity is one of our goals, it would be inaccurate to attempt to improve the empirical validity of the model by evaluating solely the macro-behavior, thereby calibrating the input parameters to unrealistic values (Fehler, 2010). Therefore, we followed the approach of validating until every validation variable (on micro and macro level) was either in a realistic range or its difference was explainable (and acceptable for the model purpose).

4.2.3 Empirical data for calibration and validation

According to Kelly et al. (2013), "Predictive models are generally required to have some level of accuracy in reproducing historic observations, and thus require data for calibration, and other independent data for validation.". In the following, we present the empirical data used in these two processes, and how these data were used.

4.2.3.1 Data from the Swiss Federal Statistical Office

A wide range of fine-grained data on the wood markets in Switzerland is provided by the Swiss Federal Statistical Office (FSO). The most valuable data for our model regards the amounts of harvested and processed wood, and the prices thereof. The following paragraphs provide an overview of these data and show how we prioritized them to validate our model.

For each of the six assortments represented in the model, data on the yearly harvested amount from 2004 until 2014 per forest owner type (public or private) in our study region, canton GR, is available. This gives us 12 values per year to use for the validation. Depending on the importance of the assortment in the study region, different priorities were assigned to them, while some even were omitted (Table 4.5). Finally, the amounts of wood processed by sawmills in the years 2002, 2007, and 2012 in our study region were used for the validation of the model (this data is only available in 5-year increments). Here, softwood is considered to be of high priority, while hardwood is considered to

be of low priority as it constitutes less than 0.5% of the total amount processed in the study region.

Forest property type	Assortment	Avg. m ³ /a produced 2004-2014	Coefficient of variation (σ/μ) 2004-2014	Validation priority
Public	Sawlogs softwood	249'097	9.6%	high
	Sawlogs hardwood	311	79.7%	low
	Energy wood softwood	65'747	27.8%	high
	Energy wood hardwood	14'130	25.7%	high
	Industrial wood softwood	7'492	13.9%	medium
	Industrial wood hardwood	328	117.0%	<i>omitted</i>
Private	Sawlogs softwood	21'089	39.5%	high
	Sawlogs hardwood	126	176.5%	<i>omitted</i>
	Energy wood softwood	5'779	48.0%	medium
	Energy wood hardwood	4'318	20.1%	medium
	Industrial wood softwood	538	45.7%	low
	Industrial wood hardwood	200	139.1%	<i>omitted</i>

Table 4.5: **Data for harvested wood available for validation.** Each row represents an assortment and thus a variable for which a time series exists for model validation. The averages and coefficients of variation (CV) are shown to indicate the relevance of the variable in the validation process. Assortments with small annual amounts (below 1000 m³) are considered low priority. If there is a high variation in addition, the assortment is omitted from the validation.

Price data for all six simulated assortments were used for validation. This data is available on a quarterly basis from 2001 to 2014. The validation priorities are based on these for the amounts (Table 4.5): prices for sawlogs (softwood) and energy wood (softwood and hardwood) are considered high priority; industrial wood (softwood) medium priority; the rest is low priority.

4.2.3.2 Data from own surveys

Six surveys were conducted to obtain detailed insights into the market participants' behavior and the market structure. The survey participants were informed that their answers to the questions in the questionnaire will be used for this research project, in an anonymized form. Table 4.6 gives an overview of these surveys: the four most important agent types in our model were surveyed, whereas the others have been built based on expert knowledge. The key agents are the public forest managers, as they manage the biggest part of the forest area (70% in the whole country, 88% in our main study region of canton GR (BFS, 2015a)), while also providing advice to private forest owners; therefore, they have the main control of the wood supply. They were surveyed in a full population survey in three different regions. Because of the peculiarities of these regions, different results for each region were expected and confirmed empirically. The respondent rate of this agent group was high (approximately 70-75%). The public

forest manager survey in the regions AG (canton of Aargau) and GR (canton of Grisons) were completed on paper as an additional agenda item on the semiannual public forest manager meetings, where most of the public forest managers of the corresponding region were present. These meetings took place in March and April 2014. For the region BE (canton of Bern), a mail containing a link to the online survey was sent to all public forest managers in the region. This survey was online in December 2015.

	Region	N	n	Year	DCE included
<i>Suppliers</i>					
Public Forest Managers	AG	ca. 80	55	2014	yes
Public Forest Managers	GR	ca. 90	68	2014	yes
Public Forest Managers	BE	ca. 100	77	2015	yes
Private Forest Owner	BE	ca. 36'000 (contacted: 1'440)	69	2016	no
<i>Demanders</i>					
Sawmill Operators	CH	ca. 400	21	2015	yes
Energy Wood Buyers	CH	ca. 2000 (contacted: 744 ^a)	112	2016	yes

^a 744 public forest managers were contacted and asked to forward the survey to their main energy wood buyer.

Table 4.6: **Overview of conducted surveys.** Regions AG, GR, and BE correspond to cantons in Switzerland; CH corresponds to Switzerland as a whole. The last column states whether a discrete choice experiment (DCE) was included in the survey.

The survey participants in the private forest owner survey were recruited in March 2016 by sending them a letter with a link to an online survey. In this survey, the response rate was low (4.8%). The answers revealed that those responding seem to have a very strong relation to their forest, and this is, according to expert opinion, a minority in Switzerland. Thus, the survey results are highly likely to have a strong sample selection bias (Heckman, 1979). The results of this survey were, therefore, omitted from the use in the model.

The sawmill operators survey was sent by e-mail as a pdf form to the members of the Swiss association of the timber industry in April 2015. While the response rate of this survey appears rather low at first glance (5.25%), our sample covers 41% of the countrywide processing capacity. This can be explained by the power-law distribution of the sawmill sizes. In 2014, approximately 1.87 million m³ of sawlogs were cut in Switzerland (BFS, 2015b). Approximately one third of this was processed in sawmills with an annual cut below 10'000 m³, one third between 10'000 m³ and 100'000 m³, and one third above 100'000 m³. We cover 11% of the processed quantity of the first class, 14% of the second class, and 100% of the class with the largest sawmills.

The energy wood buyers had to be contacted indirectly via public forest managers. A letter was sent to them in January 2016 and they were asked to forward a second letter with a link to the survey to their main energy wood buyer. This approach obviously already reduced the number of energy wood buyers that received the survey, but was

the only possibility to get in contact with the energy wood buyers. However, the data quality of the 112 answered surveys was good and the survey provided valuable data for the model.

In the following paragraphs, we present which study results were used for which purpose in the model; some were used for model calibration, while others were used as validation data. Whenever we assumed that the model could predict a behavior that could potentially be falsified by a survey result, we used this survey result as validation data. For a few variables, only the average (over all agents) was validated; for most others, the distribution was also included by taking the interquartile range (IQR) into account, i.e., the range in which 50% of the values lie. The consideration of the IQR as an additional measure aims at improving the confidence in the model, as averages alone do not provide information about the variation, and even can be misleading if the underlying distribution is skewed.

Public forest manager surveys: From the three public forest manager surveys conducted, mainly the results from the study in canton GR were integrated into the model. While canton AG is flat terrain, canton GR is mountainous, which leads to large differences in these wood markets (e.g., owing to different harvesting costs). Therefore, differences in the results of these two surveys were used to identify parts of the model that need to be parameterizable, so that the model can be used in the future to simulate different regions. The survey in canton BE contained an additional section where public forest managers were asked questions regarding their mentoring of private forest owners. These results were used to compensate for the inapplicable private forest owner survey. Table 4.7 gives an overview of the results relevant to the model, and how they were used.

Survey element	Use	Details
Discrete Choice Experiment	Input / Calibration	Basis of the decision model of the public forest manager agents and private forest owner agents.
Percentage of wood reserved for regular customers (not bound by contract)	Input / Calibration	This variable is important for the conclusion of contracts between business partners with no prior knowledge of each other. The following averages were used: sawlogs: 42%, energy wood: 55%, industrial wood: 25%
Own consumption of private forest owners per assortment	Input / Calibration	Averages used: sawlogs: 10%, Energy wood: 60%, industrial wood: 5%
Number of incoming requests per year (per assortment)	Validation	Averages (IQR in brackets): sawlogs: 5 (2-9), energy wood: 12 (1-20), industrial wood: 1 (0-2)
Percentage of incoming requests per year that were rejected (per assortment)	Validation	Averages (IQR in brackets): sawlogs: 25% (0-40%), energy wood: 20% (0-40%), industrial wood: 30% (0-50%)

Table 4.7: Survey results from the public forest manager surveys and their use in the model.

Sawmill operators survey: The data from the sawmill operators survey and their use in the model are listed in Table 4.8. Some of the results are used as stylized facts (cf. Janssen and Ostrom, 2006).

Survey element	Use	Details
Discrete Choice Experiment	Input / Calibration	Basis of the decision model of the sawmill agents
Stock capacity	Input / Calibration	A full warehouse covers the demand for two months.
Utilized stock capacity	Validation	64% on average
Duration of business relationships	Validation	Stylized fact: business relationships are usually long-term (>10 years).
Percentage of transportation costs in relation to the total costs per purchased m ³ .	Validation	Average 15%, IQR 12-17%.
Supply perimeter (distance between plant and forest where >90% of the wood is sourced).	Validation	Average 43 km, IQR 25-50 km
Number of incoming requests per year	Validation	Average 25, IQR 6-43
Number of outgoing requests per year	Validation	Average 10, IQR 2-14
Percentage of annual delivery quantity per supplier type	Validation	Averages (IQR in brackets): Public Forest Managers: 42% (20-66%) Bundlers: 38% (6-52%) Traders: 20% (14-26%)
Annual delivery quantity of a single supplier per type (the amount one sawmill obtains from one supplier)	Validation	Averages (IQR in brackets): Public Forest Managers: 600 m ³ (250-950 m ³) Bundlers: 3700 m ³ (1063-5600 m ³) Traders: 1150 m ³ (400-1570 m ³)

Table 4.8: Survey results from the sawmill operators survey and their use in the model.

Energy wood buyers survey: Table 4.9 gives an overview of the energy wood buyers survey results and their use in the model.

4.2.3.3 Case study

As a further validation step, we use the model in the context of a historical case of a very large sawmill entering the market in our study region and becoming insolvent only a few years afterwards. The sawmill was located in the Domat/Ems, a village in our study region located at a national highway, and the site also had direct access to the railways which should reduce transportation costs. The sawmill started operating in 2007, sawlogs were delivered to the site starting in October 2006 (Suedostschweiz, 2015). It was the largest sawmill ever built in Switzerland, having a processing capacity approximately three times higher than the previously largest sawmill. The sawmill had

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Survey element	Use	Details
Discrete Choice Experiment	Input / Calibration	Basis of the decision model of the energy wood buyer agents
Contract duration	Input / Calibration	Usually 5 to 15 years (10 years on average)
Share of softwood in total wood amount processed	Input / Calibration	Study region: 85% softwood, 15% hardwood (whole country: 50% softwood, 50% hardwood)
Stock capacity	Input / Calibration	A full warehouse covers the demand for one month.
Duration of business relationships.	Validation	Stylized fact: business relationships are usually long-term (87% >5 years, 60% >10 years)
Supply perimeter (distance between plant and forest where >90% of the wood is sourced).	Validation	Average 15 km, IQR 5-20 km
Imported amounts	Validation	Import of energy wood is very unusual
Number of incoming requests per year	Validation	Average 1.5
Number of outgoing requests per year	Validation	Average 1

Table 4.9: Survey results from the energy wood buyers survey and their use in the model.

difficulties to purchase sufficient amounts of sawlogs to be profitable, which finally lead to its insolvency in 2010 (Suedostschweiz, 2015). Using this case as an additional validation step, we want to check whether the model is able to reproduce the fact that the sawmill was not able to obtain sufficient sawlogs to become profitable in the time that it was on the market.

4.3 Results and discussion

First, this section describes the results of the model validation with a focus on historical data validity (by comparing the model output to the empirical data presented in the method section) and event validity (by reproducing the historical event described in the case study). Then, additional insights gained by simulating the case study are presented. As the model is stochastic, all simulation results presented here represent the average of 100 runs.

4.3.1 Validation

4.3.1.1 Amounts

Fig 4.4 shows the simulated amounts produced and processed in comparison to the actual historical amounts for the assortments considered high or medium validation priority; the figures for the assortments considered low validation priority are shown in the appendix. The model is able to approximate the trends of the actual variable values over the evaluated period.



Figure 4.4: **Comparison of actual historical and simulated data over time.** The diagram at the top and at the bottom left show produced and processed amounts classified as high-priority for validation, and the diagram at the bottom right the processed amounts classified as medium priority. The diagrams show that the model is able to approximate the trends of produced and processed amounts in the specified validation period with a sufficient level of accuracy.

The main factors influencing wood production in the model are prices. Higher absolute prices increase the production by allowing wood harvesting in regions with higher harvesting costs, e.g., in mountainous terrain. The relative price levels of the different assortments shift the shares of the produced assortments (sawlogs, energy wood, and industrial wood). Private forest owners thereby have a wider scope than public forest managers, i.e., the shifting of the shares of the different assortments can be larger. These price elasticity parameters were not known and, therefore, needed to be cali-

brated indirectly (cf. section 4.2.2.1) to match the available empirical data regarding system behavior.

The top-left diagram in Fig 4.4 shows the processed amounts in the study region in the years 2002, 2007, and 2012, together with the harvested amounts from 2004 to 2014. The bulk purchaser analyzed in our case study was on the market from 2007 to 2010, which explains the processing peak in 2007. The differences between production and sawn wood in the years before and after also show why such a bulk purchaser was expected to mobilize more wood in the study region.

The validation results presented in Fig 4.4 show how closely the historical data can be approximated by the model. This is important for the requirement that the model must be able to show how wood availability can be increased. While price elasticity plays an important role therein, it is not the only factor: given the mountainous terrain of our study region with hardly-accessible areas, a higher production level is only possible by accepting higher harvesting costs, which again affects the decisions of the agents.

4.3.1.2 Prices

International wood prices and the exchange rate between the study region and adjacent countries are exogenous variables in the model, and the prices in the study region depend largely on international prices of the assortments. Therefore, it is a challenge for the model to reproduce local prices during periods when they differ from international prices. This was mainly the case around the time of the market presence of the bulk purchaser analyzed in the case study. The largest differences between local and international prices were observed for the most important assortment, sawlogs softwood. Fig 4.5 shows that the model is able to approximate the historical local prices of the six simulated assortments.

An important endogenous variable influencing the local prices on the supply side is the annual harvested amount, which influences harvesting costs and, thereby, the supply price. On the demand side, insufficient degrees of capacity utilization increase the willingness to pay and vice versa.

The ability of the model to reproduce local prices is relevant for the goal of understanding resource availability and allocation, as prices are a crucial factor in the decision model of every agent.

4.3.1.3 Validation data from own surveys

Table 4.10 summarizes the extent to which the model was able to replicate the empirical data from the surveys presented in the method section. The majority of the results could be reproduced in an acceptable range; the reasons for larger discrepancies are explained. Validating the model with this empirical data is important because structural validity has a high relevance for our modeling purpose of system understanding, in particular, obtaining better insights into the processes of resource allocation. Averages and IQRs were calculated at each simulated time step over all agents of the concerned type. Finally, these values were averaged over the whole simulation period.

CHAPTER 4. EMPIRICAL VALIDATION OF AN AGENT-BASED MODEL OF WOOD MARKETS IN SWITZERLAND

Survey question	Values from surveys (average, IQR in brackets when relevant)	Simulated values	Rating (+,0,-)
Public Forest Manager Survey			
Number of incoming requests per year (per assortment)	Sawlogs: 5 (2-9) Energy wood: 12 (1-20) Industrial wood: 1 (0-2)	5.2 (2.4-7.4) 4.7 ^a (1.8-6.6) 0.4 (0-0.4)	+
Percentage of incoming requests per year that were rejected (per assortment)	Sawlogs: 25% (0-40%) Energy wood: 20% (0-40%) Industrial wood: 30% (0-50%)	57%, (28-94%) 65%, (36-97%) 45%, (6-85%)	- ^b
Sawmill Survey			
Utilized stock capacity	64%	77%	+
Duration of business relationships	Stylized fact: business relationships are usually long-term (>10 years).	Affirmed	
Transportation costs in relation to total costs per purchased m ³	15% (12-17%).	16% (10-20%)	+
Supply Perimeter	43 km (25-50 km)	44 km (30-54 km)	+
Incoming Requests	25 (6-43)	27 (19-32)	+
Outgoing Requests	10 (2-14)	9.0 ^c (7.6 - 9.9)	+
Percentage of annual delivery quantity per supplier type	Public forest managers: 42% (20-66%) Bundlers: 38% (6-52%) Traders: 20% (14-26%)	45% (26-64%) 37% (14-57%) 18% (4-27%)	+
Annual delivery quantity of a single supplier per type ^d	Public forest managers: 600 m ³ (250-950 m ³) Bundlers: 3700 m ³ (1063-5600 m ³) Traders: 1150 m ³ (400-1570 m ³)	1982 m ³ 6550 m ³ 1452 m ³	+ ^e
Energy Wood Buyers Survey			
Duration of business relationships	Stylized fact: business relationships are usually long-term (87% >5 years, 60% >10 years)	Affirmed	
Supply perimeter	15 km (5-20 km)	19 km (10-22 km)	+
Imported amounts	Import of energy wood is very unusual	8% is imported	0 ^f
Incoming requests per year	1.5	12	- ^g
Outgoing requests per year	1	18	- ^g
^a Energy wood buyers are aggregated agents in the model, which may cause the discrepancy to the survey. ^b An explanation for this discrepancy is that, in reality, market participants might have a better sense of which public forest manager is the most promising for the next transaction. Calibrating the model for these variables was difficult: with data-mining techniques, heuristics were found and integrated into the agents' decision model, which at least lowered the discrepancies to the empirical values. ^c For the calculation of the average (but not of the IQR), the bulk purchaser of the case study was excluded. ^d This variable was only evaluated for the bulk purchaser of the case study. Besides this large sawmill, there are only very small sawmills in the study region, which are on the one hand usually supplied by only a few suppliers, on the other hand underrepresented in our survey. ^e The values for bundlers and traders are around the upper limit of the IQR, which is acceptable. The value for public forest managers is approximately twice as high as the upper limit of the IQR. This can be explained by the forests in our study region GR, which consist of approximately 90% softwood. In contrast, the survey has been conducted over the whole of Switzerland, where forests consist of approximately 50% softwood. Therefore a typical public forest owner in GR has almost double the amount of softwood available, and softwood is what sawmills are mainly processing. This explanation was confirmed by simulations with the share of softwood set to 50%; then, the value for public forest managers was also around the upper limit of the IQR. ^f Approximately two thirds of the study region's border is an international border; therefore, some border regions may import wood from the adjacent neighboring country. ^g Energy wood buyer agents are aggregated agents in the model and therefore represent multiple real-world buyers at all scales, whereas the survey participants were large-scale heating plant operators. They usually have one or a few long-term contracts, whereas smaller energy wood buyers may buy their energy wood as required.			

Table 4.10: Comparison of empirical data from surveys with simulation data.

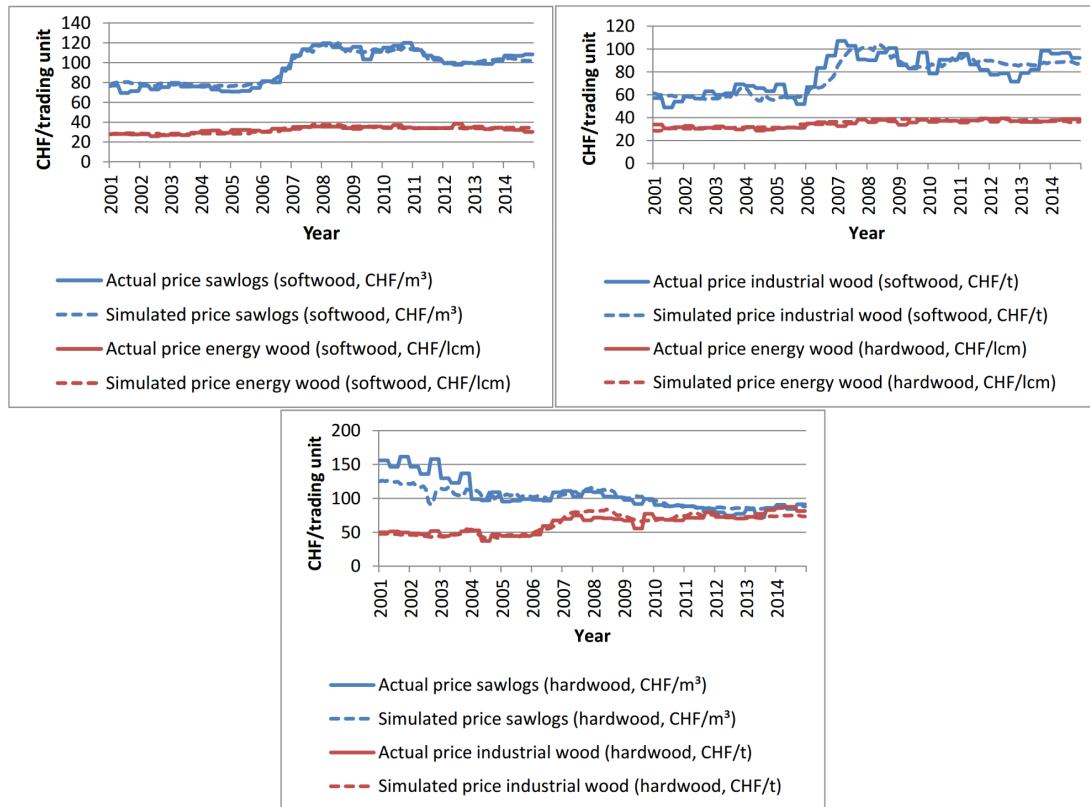


Figure 4.5: **Simulated prices compared to the actual historical prices from 2001-2014.** While the model internally always operates in m³, the prices are expressed here per trading unit, which depends on the assortment (lcm = loose cubic meters). In the first 2-3 years simulated, the model needs to settle, which explains the gaps between the actual and simulated values at the beginning of the simulation.

4.3.1.4 Case study

The model was able to reproduce the fact that the large-sized sawmill was not able to reach a profitable degree of capacity utilization during the time it was on the market. The simulated amounts supplied to the sawmill are shown in Fig 4.6.

The reasons why the sawmill was not able to purchase sufficient wood already became apparent during the model-building process. Our surveys showed that existing business relationships are relatively stable, and the majority of the annual harvested wood is already reserved for regular customers, even without contracts. Trust plays an important role in the Swiss wood markets (Kostadinov et al., 2014); therefore, wood suppliers are cautious regarding new contract partners and aim to preserve their business relationships with existing regular customers. Hence, a new market player first has to gain the wood suppliers' trust by buying low amounts and proving his reliability. With increasing trust, the new player will be able to buy increasing amounts of wood. This is a slow process, and is especially critical if the new player is a bulk purchaser that needs to process large amounts of sawlogs to be profitable.

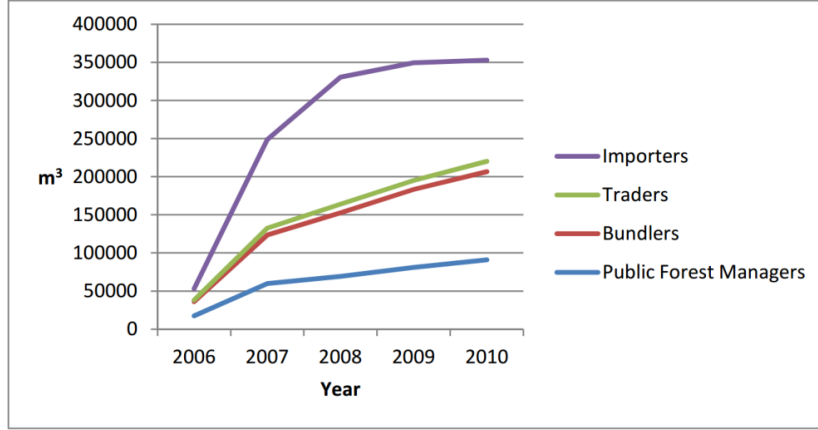


Figure 4.6: **Stacked chart showing the simulated amounts supplied per supplier type for the sawmill under study.** The capacity of the sawmill was approximately 800'000 m³ per year; therefore, the simulated degree of processing capacity utilization in 2010 was approximately 44%. Our surveys showed that large sawmills in Switzerland have a degree of capacity utilization of approximately 85% on average.

Looking at the data of the produced amounts used for validation, an increase in wood production could be observed when this bulk purchaser became active in the market. The additionally harvested wood could have been supplied to the bulk purchaser, while still satisfying existing business relations. However, in reality, according to expert knowledge, this wood was mainly exported – this was also the case in our simulations.

4.3.2 Additional insights

Our simulations of the case study showed that this sawmill not only had difficulties in being supplied with sufficient amounts of wood, but was also required to pay approximately 9% more than its competitors on average. If the willingness to pay was reduced (by changing β_0 in the decision behavior of the agent, i.e., the utility threshold for accepting an offer or rejecting it) so that the sawmill paid prices similar to those its competitors paid, the total amount supplied per year dropped to approximately 100'000 m³.

In our surveys, we observed that public forest managers have a certain percentage of sawlogs that they reserve for regular customers, even without a contract in place. This parameter has a value of 42% in our study region GR and is even higher (62%) in the two other regions surveyed, AG and BE. Surprisingly, reducing this value to zero does not change the sawmill's supply rate considerably, but lowers the supply prices that the sawmill is required to pay. A combination of several reasons may explain this observation: first, not reserving wood for regular customers does not prevent that wood from still being sold to these customers. Second, such reservations are not absolute, meaning that at some point during the year, when, e.g., the demand of regular customers turns out to be lower than expected, the previously reserved amount

may be sold to any customer. Third, if a non-regular customer pays a good price, parts of the reserved amounts are usually sold. Therefore, if public forest managers reserve less for regular customers, other consumers are not necessarily able to buy more, but at a lower price.

Another interesting phenomenon is observed when this parameter is set to 100%, i.e., when public forest managers reserve all their sawlogs for regular customers. The sawmill now needs to pay substantially more to obtain sufficient wood. While the increased prices the sawmill pays still do not persuade the domestic public forest managers to provide the sawmill with more wood, the imported amount now increases considerably. This finally leads to an even higher degree of processing capacity utilization than when nothing is reserved for regular customers, but only under the assumption of a high willingness to pay – a situation that probably also would have led to a market exit.

While in section 4.3.1, the model’s extent of replicative and structural validity was analyzed, this section aimed at predictive validity, i.e., showing examples of how the model can be used to predict system behavior that is not yet known (according to the definition of prediction by Kelly et al. (2013)).

4.4 Conclusions and outlook

We presented an agent-based model of wood markets in Switzerland, described the validation procedure, and showed to what extent the model is able to reproduce empirical data on amounts, prices, survey results on structural data, and a specific historical market event. The outcome of the rigorous validation qualifies the model to simulate scenarios concerning resource availability and allocation in a given region.

We further showed that ABM is an appropriate modeling method for this type of market, as the system behavior can be modeled as it emerges from the decision behavior of the agents, which is in turn also affected by macro-level variables. The possibility of observing market participants on any level of aggregation is a clear advantage, as we can – for example – check whether not only on average demanders are sufficiently supplied, but also how the supply is distributed on the individual level. Finally, the possibility of modeling transport routes using data from the real road network in the study region is useful, as transportation costs are an important factor for a resource with a relatively low ratio of price per physical mass and volume.

In accordance with Edmonds and Moss (2004), we believe that there are two diametrically opposed ways to build a model such as the one presented here: the KISS strategy (“keep it simple, stupid!”) and the KIDS strategy (“keep it descriptive, stupid!”). We decided to use the second approach by creating a complex, but highly descriptive model. This means that we attempted to incorporate as much of our knowledge as possible regarding the market participants and the conditions under which they operate. While this approach makes the model more complex in terms of communication and analysis, it avoids an a priori simplification, which may lead to a model that does not include the relevant phenomena (Edmonds and Moss, 2004). In addition, we experienced that the process of gathering as much data and knowledge as possible during the model-building

process can have additional advantages: in our case, the reasons for the failure of the sawmill analyzed in the case study already became apparent before the first simulations were conducted. This shows that not only the model as the final artefact, but also the modeling process, can provide important insights into the system under study, making the journey a considerable part of the reward.

In the future, the model will be used to analyze scenarios relevant to stakeholders and policy makers, concerning – for example – the influence of intermediaries and the effects of set-aside scenarios.

4.A Appendix

4.A.1 Simulated amounts for assortments with low validation priority

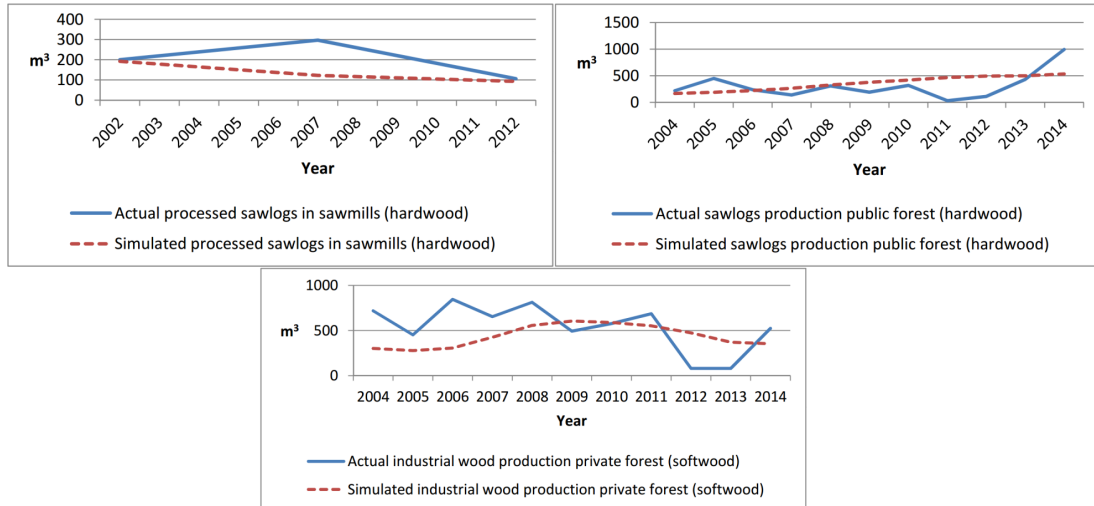


Figure 4.7: Comparison of actual historical and simulated data over time for the assortments considered low validation priority.

An Agent-Based Model of Wood Markets: Scenario Analysis

Holm, S., Thees, O., Lemm, R., Olschewski, R., & Hilty, L.M. (2018). An Agent-Based Model of Wood Markets: Scenario Analysis. Submitted to *Forest Policy and Economics*¹.

Abstract

We present an agent-based model of wood markets. The model covers softwood and hardwood markets for sawlogs, energy wood, and industrial wood. Our study region is a mountainous area in Switzerland that is close to the border, and therefore partially depends on the wood markets of the adjacent countries. The wood markets in this study region are characterized by many small-scaled wood suppliers, and a mix of private and public-owned forests. The model was developed to investigate the availability of wood in the study region under different market conditions. We defined several scenarios that are relevant to policy makers and analyzed them with a focus on the two most important assortments of wood in the study region, sawlogs softwood and energy wood softwood. The development of the prices and amounts sold in the scenarios are compared to a business-as-usual scenario. The scenarios were designed to investigate i) the influence of intermediaries, ii) the influence of the profit-orientation of forest owners, iii) the influence of the exchange rate, and iv) the consequences of set-asides in the study region. We conclude that the presented model has a large potential to support the planning of political measures as it allows capturing emergent phenomena, and thereby facilitates identifying consequences of political measures planned prior to their implementation.

5.1 Introduction

Computer simulation has been an important means in forestry since decades: in the 1960s already, a wide range of topics were modeled and simulated. Amongst others,

¹Shortly before this thesis was handed in, the editor of the journal rejected the paper but encouraged the authors to resubmit it after "some additional efforts of updating, revising, and editing".

growth models, forest fire protection models, and harvesting machine simulation models (Newnham, 1968)) were developed. Until today, not only the domains of application and modeling purposes have substantially widened, but also the types of simulation techniques applied, making use of the continuously increasing computational power. For example, system dynamics approaches have been used to simulate wood market scenarios (Schwarzbauer and Stern, 2010) or Monte-Carlo simulations to analyze uncertainties in forest conservation set-aside scenarios (Kallio, 2010).

In this paper we present a model of wood markets using the agent-based modeling (ABM) approach. ABM differs from other simulation approaches owing to its bottom-up perspective that allows each agent (in our case, each market participant) to be modeled individually (micro level). Simulating all agents together creates a system behavior due to their interactions. This approach has several advantages, such as the possibility to model the market in a natural and descriptive manner (as an interplay of many autonomous acting agents with different goals) or to capture emergent phenomena on any level of aggregation (macro level) (Bonabeau, 2002; Janssen and Ostrom, 2006; Macal and North, 2014). Because of these reasons, ABM is widely used in economics (where it is sometimes referred to as agent-based computational economics, cf. Tesfatsion, 2006): for example, there are many models related to electricity markets (cf. Weidlich and Veit, 2008). There are even suggestions to model whole economies with the ABM approach (Farmer and Foley, 2009). In comparison to other simulation approaches, ABM though requires more computational power, which made this method popular only in the recent 10-20 years.

Climate change and derived megatrends, such as energy transition and bio-economy, result in increasing requirements concerning the utilization of forest wood resources. Nevertheless, the sustainable potential of forest wood in Switzerland is currently not used. This situation is strongly related to the market conditions. Considering this background, our model was developed for a better understanding of the markets of forest wood, with a focus on the resource availability and allocation of different assortments. It was the objective to establish an agent-based model and to apply the model to regional wood markets. The study region presented is Grisons in Switzerland, a mountainous region located in the border of Switzerland. In the scenario analysis presented, different market situations were analyzed in terms of their impact on the markets of sawlogs and energy wood.

An explorative study by Kostadinov et al. (2014) showed that agent-based modeling is a suitable method to analyze wood markets, particularly considering the peculiarities of our study region. The new version of that model presented here addresses some important improvements. We solved the model boundary problem, implemented a transport route model which calculates transport costs based on real road and rail routes in the study region, and gathered empirical data on the market participants' decision behavior with discrete choice experiments (Carson and Louviere, 2011; Louviere et al., 2010) and surveys. Additionally, the conceptual model was extended (more agent types, more markets), a rigorous validation was conducted, and finally the performance of the model was significantly improved, allowing faster scenario simulations with more agents. Details on these improvements are described in Holm et al. (2018).

Considering the above improvements, the model can now be used for policy analysis by simulating and analyzing politically relevant scenarios. In section 5.2, we define a set of such scenarios after providing an overview of the study region and the most important characteristics of the model. Further, we present the variables observed to analyze these scenarios and describe the simulation procedure. Section 5.3 first presents the results of the scenario simulations on the level of variables observed, then summarizes and discusses these results per scenario, and section 5.4 concludes the paper.

5.2 Material and Methods

In this section, we first describe the study region and the most relevant parts of the model, followed by the simulated scenarios and their relevance to the forest sector in the study region, and finally the observed variables and the simulation procedure.

5.2.1 Study Region

The study region is the canton of Grisons, a mountainous region in eastern Switzerland, located in the border of Austria and Italy. Forestry in Grisons is characterized by a high percentage of public (communal) forests (88% of the total forest size of 195'494 ha), subsidized protection forests (61% of the total forest size), and a high percentage of softwood (91%) (Olschewski et al., 2015). The wood market is characterized by bundling organizations on the supply side. On the demand side, there are small-scale sawmills in Grisons, and larger sawmills in the neighboring Swiss cantons and in the neighboring countries Austria and Italy, to where a high percentage of the wood is exported. The total annual cut is approximately 500'000 m³ and the most important assortment is sawlogs softwood. More detailed information about the study region can be found in Olschewski et al. (2015).

5.2.2 Description of the Market Model

The model depicts the markets for sawlogs, energy wood, and industrial wood in the canton of Grisons. Figure 5.1 shows (i) the combined markets of the main products (distinguishing between softwood and hardwood) and (ii) the nine different agent types. All the agents have a fixed geographical location, which for public forest managers reflects their real-world position; for other agents, the position is randomly assigned at the beginning of a simulation. A single time step in the model represents one month. In each time step, agents try to negotiate new contracts and/or fulfill their existing ones. A detailed model description according to the ODD/ODD+D protocol (a standardized way to describe agent-based models, Grimm et al., 2006, 2010; Müller et al., 2013) is available in Holm et al. (2018), where the validation procedure of the model is also described. Therein, a more comprehensive description of the agents, their decision behavior, their individual goals, and how they interact is provided. For the

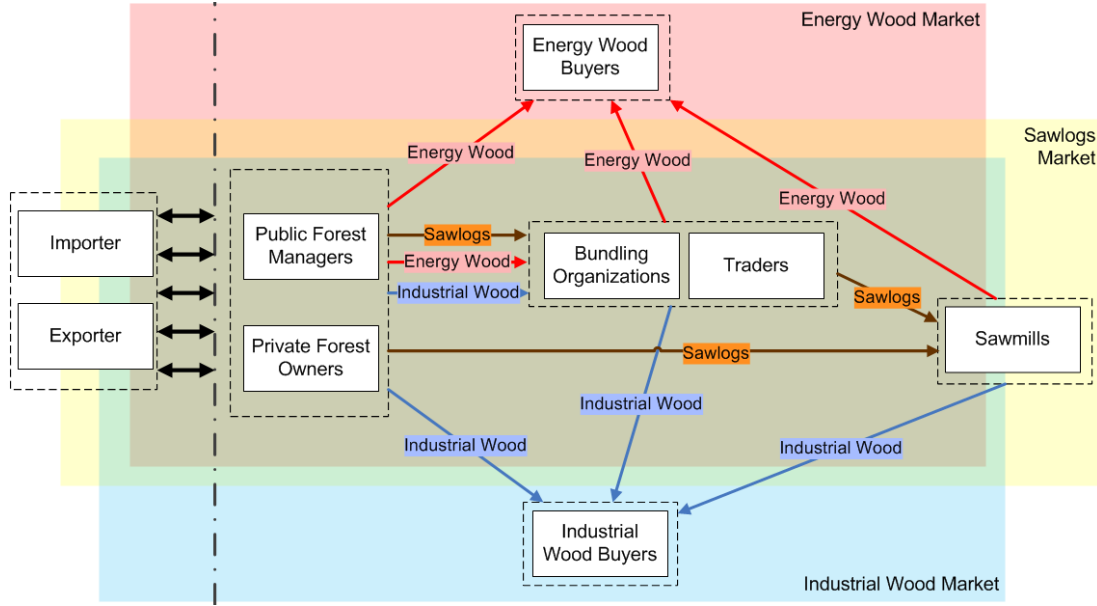


Figure 5.1: Conceptual model of the markets and the agent types.

convenience of the reader, we repeat the agent descriptions as defined in Holm et al. (2018) here:

- **Public forest managers:** These agents manage the public forests in their area. In our study region, 88% of the forest is under public ownership (BFS, 2015a), which makes them the most important agent group on the supply side of the markets. They sell wood of all six assortments.
- **Private forest owners:** In our study region, 8% of the forest is under private ownership (BFS, 2015a) (the remaining 3.5% of the forest in the study region is hybrid property). In absolute numbers, there are 10'110 private forest owners in the study region who own a total forest area of 16'517 ha (BFS, 2015a). With an average size of 1.65 ha per private forest owner, the wood is generally not harvested by the owners themselves, but with the help of public forest managers or contractors. They are often mentored by a public forest manager. In the model, these agents are aggregated such that there is only one private forest owner agent in the territory of each public forest manager, representing (for model simplicity) the aggregate of all private owners in this territory. They sell wood of all six assortments.
- **Traders:** Traders buy all six wood assortments in the model and try to sell them in the markets at a profit.
- **Bundling organizations:** These agents are cooperatives of small suppliers (private and public), structured to reduce distribution costs and increase market power. They are modeled as intermediaries who are strongly linked to the affiliated suppliers.

- **Sawmills:** They buy sawlogs and process them into different wood products (for which the downstream markets are not included in the model). During the processing of sawlogs, residuals (tree bark, woodchips, shavings, and sawdust) are accumulated as byproducts and either used by the sawmill itself or sold on the market as energy wood and industrial wood.
- **Industrial wood buyers:** They buy industrial wood and process it into products such as pulp and paper. The downstream markets are not included in the model.
- **Energy wood buyers:** They buy energy wood, predominantly for heating purposes. This includes all consumers from single-family homes with a fireside up to district heating distributors. These market participants are modeled as aggregated agents.
- **Importers:** They import wood from the outside to the inside of the modeled region.
- **Exporters:** They export wood from the inside to the outside of the modeled region.

In order to ensure simplicity, the term "forest owners" is used hereafter to represent the wood suppliers, and therefore includes both the public forest managers and private forest owners.

5.2.3 Scenario Definition

Based on a basic wood market situation, we simulated a set of economic and political relevant scenarios to analyze the influence of (i) bundling organizations, (ii) forest managers' profit orientation, (iii) exchange rates, and (iv) set-asides, on the supply of forest wood. This selection (i-iv) is the result of workshops with forestry professionals. To facilitate the discussion of the scenarios, they are denominated with a three-letter code.

5.2.3.1 Scenario BAU: Business-As-Usual

A business-as-usual (BAU) scenario is simulated to create a baseline for a comparison with other scenarios. In this scenario, all exogenous variables are fixed: the global wood prices and the exchange rate remain constant, agent quantities do not change (except for sawmills, which continuously exit the market as observed in reality in the past decades), and all model parameters are set to the values for which the model was validated in Holm et al. (2018). This concept of fixing the exogenous variables at the point where the model starts to simulate the future is often called "freezing" in literature (e.g., Hilty et al., 2006; Krewitt et al., 2007; Laitner et al., 2010).

5.2.3.2 Scenario BUN: A Market without Bundling Organizations

On the market under study, we find cooperations of wood suppliers, called "bundling organizations." They aggregate the supply of associated wood suppliers and sell the wood on their behalf. These bundling organizations have sometimes been criticized: forest owners often use bundling organizations only when they are unable to directly sell wood, such as in market situations with low demand. On the other hand, sawmills sometimes view bundling organizations as less reliable partners as they depend on the supply by forest owners, and can also be competitors as both sawmills and bundling organizations want to buy wood. In the BUN-scenario, we remove all bundling organizations from the study region at the beginning of the forest year 2017/18, which is September 1, 2017.

5.2.3.3 Scenario DEC: Influence of the Forest Owner's Profit Orientation

The decision system of the wood suppliers has been implemented on the basis of expert interviews and empirical data from discrete choice experiments. The details of this approach are explained in Holm et al. (2016). When forest owners consider selling sawlogs, they consider four decision criteria: amount of sawlogs available, amount of sawlogs demanded, trust in the demander, and financial margin. Based on the discrete choice experiments, every forest manager has individual decision parameters, and therefore different weights for these decision criteria. Some managers are more profit-oriented, while others, e.g., prefer to sell to customers they have known for years, disregarding small price differences. In this scenario, all forest managers receive new decision parameters in June 2017. These decision parameters reflect a strictly profit-oriented behavior. This scenario is relevant as the sawlogs market in our study region is, according to different expert interviews we conducted, sometimes deemed inefficient as the supply side allegedly does not behave sufficiently profit-oriented.

5.2.3.4 Scenario EUR: Influence of the Exchange Rate

This scenario is divided into two sub-scenarios, EUR080 and EUR150. They start in June 2017 and end in December 2027. During this time period, the exchange rate CHF-EUR is continuously and steadily adapted from 1.093 (the actual exchange rate in June 2017) to 0.80 CHF/EUR (Scenario EUR080) or 1.50 CHF/EUR (Scenario EUR150). In other words, the exchange rate is reduced by 0.0024 CHF/EUR per month or increased by 0.0032 CHF/EUR per month in the given time period.

The domestic wood markets, in particular in our study region that is close to the borders of Austria and Italy, are influenced by the exchange rate. Due to the continuous drop of the exchange rate since 2008 (Figure 5.2), such scenarios became politically relevant, particularly after the interventions of the Swiss National Bank (SNB, the central bank of Switzerland) to hold a certain minimum exchange rate, and thereby supporting the export industry, were suddenly stopped.

In September 2011, the SNB announced that "it will no longer tolerate a EUR/CHF exchange rate below the minimum rate of CHF 1.20" and that it "will enforce this

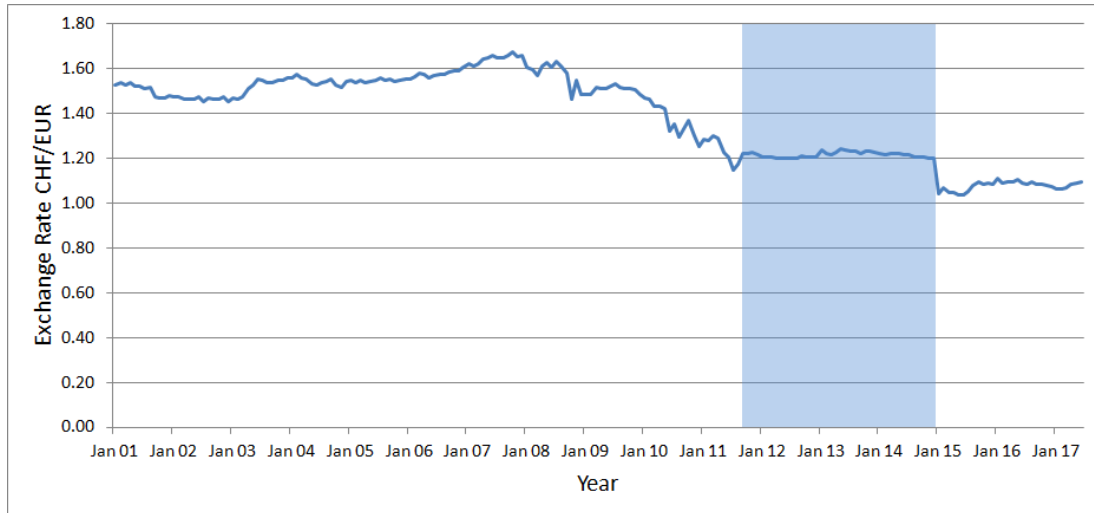


Figure 5.2: Exchange rate CHF/EUR (monthly averages). The highlighted blue area shows the period of the enforced minimum exchange rate.

minimum rate with the utmost determination and is prepared to buy foreign currency in unlimited quantities” (SNB, 2011). This minimum rate was enforced until January 2015, when the discontinuation of the minimum exchange rate was announced (SNB, 2015). This led to an immediate drop of the exchange rate to 1.00 CHF/EUR (average exchange rate of the day after the discontinuation), recovering slightly in the subsequent weeks, and stabilizing at an exchange rate of approximately 1.05 CHF/EUR (Figure 5.2). This situation was very challenging for the domestic wood sector as it made the export of wood and wood products very unattractive. It emphasizes the relevance of simulating scenarios related to exchange rate changes. Thereby, the potential impacts on the wood sector can be analyzed in a manner where measures can be planned in advance to absorb potential losses.

5.2.3.5 Scenario SET: The Consequences of Set-Asides

This scenario explores the influence of setting aside forest land, e.g. for conservation purposes, in our study region. What happens if parts of the forest are not managed anymore? Set-asides are already realized in several areas in our study region (AWN, 2017) and also in other parts of Switzerland (Gattlen, 2012). In the simulated scenario, 39% of the public forests are set aside at the beginning of the forest year 2017/18. This is the maximum as 61% of the forest area in the study region is protective forest (BAFU, 2016), which cannot be set aside. The scenario is analyzed here only from an economic perspective, not in terms of its ecological effects.

5.2.4 Observed Variables

In Holm et al. (2018), we described how we validated our wood market model. A focus of the model validation was the ability of the model to reproduce historical prices

and production amounts. The model depicts the markets of six wood assortments, namely sawlogs (softwood and hardwood), energy wood (softwood and hardwood), and industrial wood (softwood and hardwood). In this paper, we focus on the two most relevant assortments in our study region, sawlogs softwood and energy softwood. Together, they account for approximately 93% of the wood assortments produced in the study region (BFS, 2017).

As the model was able to reproduce historical prices and production amounts to a sufficiently large degree, we also focus on the amounts and prices for scenario evaluation. The following variables are observed in our study region, both for sawlogs and energy wood:

- Amounts sold annually by public forest managers and private forest owners
- Prices paid by demanders.
- Sales volumes of the two intermediaries in the model, bundling organizations and traders.

In the results section, the development of these variables in the different scenarios are compared and analyzed.

5.2.5 Simulation Procedure

The different phases of our simulations are illustrated in Figure 5.3: our simulations start in the year 2001 and end in 2027. After the simulation starts, the model requires 2-3 years to settle down (aspects such as business relationships between agents need to be established). The subsequent simulation period, 2004 to 2016, was used to validate the model (the validation process of the years 2004-2014 is described in Holm et al. (2018)). The scenarios defined above are triggered in the year 2017, as at the time of writing most of the exogenous parameters (e.g., the actual exchange rate) until that year are known, and therefore the scenarios are used for an outlook of 10 years into the future.

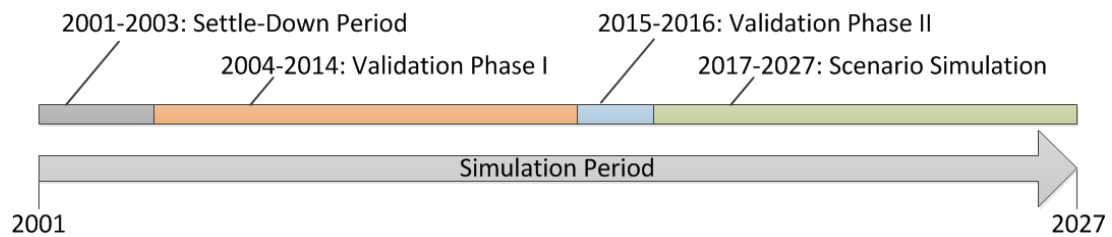


Figure 5.3: Simulation phases. All scenarios are triggered in 2017 and evaluated for the subsequent 10-year period.

5.3 Results and Discussion

The results presented here are grouped by the observed variables explained in the method section. All the results represent an average of 100 simulation runs as the model is stochastic. All figures in this section represent the amounts sold or prices paid of the agents *inside* the study region. It is necessary to emphasize this as there are also agents in the model who are located outside the study region and nevertheless interact with the agents inside the study region. This approach is used to avoid boundary effects and is described in detail in Holm et al. (2018).

5.3.1 Sawlogs

5.3.1.1 Prices

Figure 5.4 shows the prices paid for sawlogs (softwood) by sawmills in the study region under different scenarios. The thick black line shows the actual historical prices of sawlogs from 2001 to 2016.

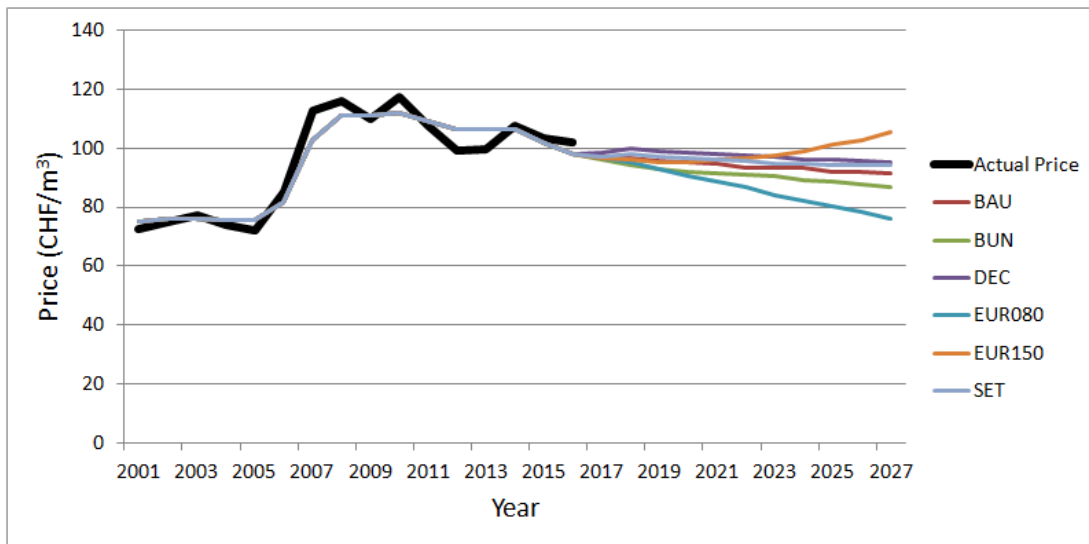


Figure 5.4: Prices paid for sawlogs (softwood) by sawmills.

The scenarios leading to the maximal divergences of prices are the two EUR-scenarios. As approximately two thirds of the study region's border is an international border, the wood prices in the study region strongly depend on international wood prices, and on the import and export of wood. Therefore, a lower exchange rate leads to lower local wood prices, and a higher exchange rate results in higher local wood prices. According to the model, the effect of a rising exchange rate is lower in comparison to a decreasing exchange rate. This can be explained by the market power of the demanders: the total demand in the study region is much less in comparison to the total supply.

In the other scenarios, including BAU, the prices slightly drop over the years at a similar rate. However, at the beginning of the scenario simulation in 2017, they divert

marginally from each other: the lowest prices appear in the BUN-scenario, marginally higher in the scenarios BAU and SET, and highest in the DEC-scenario. Lower prices in the BUN-scenario can be explained by the provision of 2-5 CHF/m³ that bundling organizations usually take for their broker-like services. Without bundling organizations, forest owners therefore can retain this provision and sell wood at slightly lower prices (while continuing to not provide the full provision as discount to the demanders, as without bundling organizations, forest owners have to identify buyers themselves, which is challenging under conditions of a "buyer's market"). Prices in the SET-scenario are approximately 2% higher in comparison to the BAU-scenario, which can be explained by the reduction of supply, and thereby less competition between the suppliers. Even higher prices appear in the DEC-scenario, where they are approximately 3.5-4% higher in comparison to the BAU-scenario. A stronger profit-orientation of forest owners in this scenario leads to these higher prices.

Why do the scenarios BAU, BUN, DEC, and SET only divert in 2017/18, and afterwards the curves remain approximately parallel? The scenarios BUN, DEC, and SET all start in 2017, i.e. at that time exogenous model variables were changed. After this change, there is a short phase where the agents adapt themselves to the new situation. In this short period of time, the four scenarios diverge. Subsequently, there are no more changes of exogenous variables, and therefore the curves remain approximately parallel.

5.3.1.2 Amounts

Figure 5.5 shows the amounts of sawlogs (softwood) sold by public forest managers and private forest owners in the study region. The thick black line shows the actual historical values of *harvested* sawlogs from 2004 to 2016. Harvested and sold amounts of sawlogs are generally equalized in the long run. The small differences in the individual years can be explained by the time between harvesting and selling (sawlogs are generally stocked in the forest between 1 and 6 months), and annual cut off.

In the BAU-scenario, the annual amount of sawlogs sold remains constant over the years (after the triggering of the scenarios in 2017). The largest divergences are observed in the EUR-scenarios and the SET-scenario: a higher exchange rate leads to higher amounts sold, a lower one to lower amounts sold. The impact of a lower exchange rate is stronger than the one of a higher exchange rate: if forest owners are forced to lower their prices, they harvest less wood. On the other hand, even with increasing prices, forest owners are not able to immediately sell much more wood as they do not have the capacity for it. In the SET-scenario, where 39% of the public forest is set aside on September 1, 2017, the sold amount unsurprisingly drops by 39%. In the scenarios BUN and DEC, the amounts sold are approximately 3-4% higher than in the BAU-scenario. Considering the BUN-scenario, this can again be explained by the fact that a bundling organization generally takes 2 to 5 CHF (approx. 2-5 USD) as provision. If forest owners are not required to pay this provision, they can retain a part of the provision for themselves and pass on the other part to the buyer by selling at lower prices. In this manner, the seller gets more money and the buyer pays less, which leads to more sawlogs being sold by forest owners. Considering the DEC-scenario, the

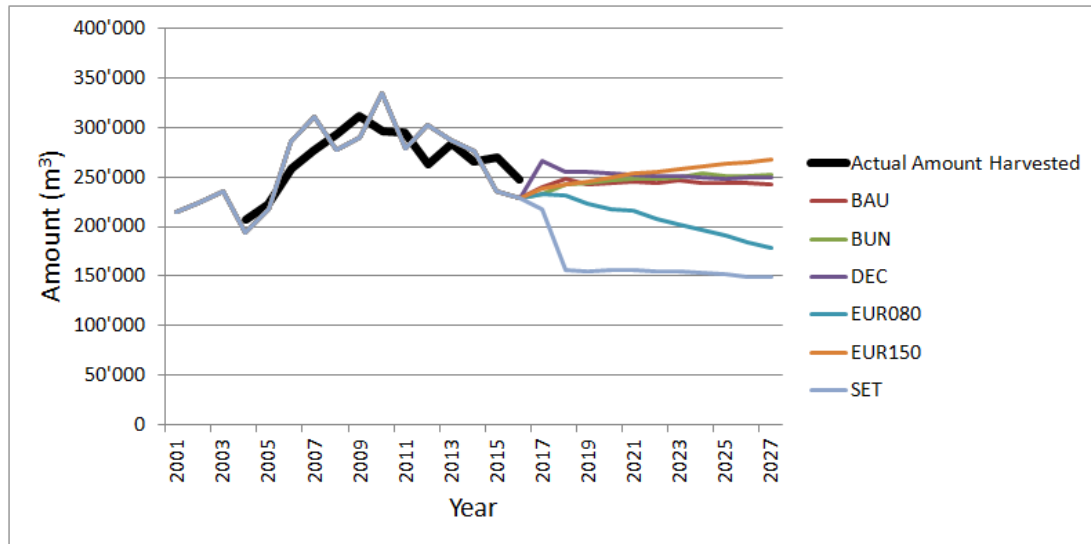


Figure 5.5: Amount of sawlogs (softwood) sold by forest owners.

increase in the amounts sold can be explained by higher prices for the forest owners as well.

5.3.1.3 Intermediaries

Figure 5.6 shows the amount of sawlogs sold by intermediaries in the study region. For this data, the actual historical values are unknown. The remarkable peak between 2007 and 2010 for the wood sold by bundling organizations can be explained by a bulk consumer who was active in the study region during that time period (in the municipality Domat/Ems) (Suedostschweiz, 2015), who presumably bought a significant amount of wood from bundling organizations. Bundling organizations sell wood as soon as they have a demander and one or several suppliers who they can "connect." Therefore, they do not have the risk of having a stock that is hardly sellable. However, traders buy and sell "at their own expense," which could be the reason why they profited less from the bulk consumer who was a strong market player (and was considered oversized from many market actors and indeed became insolvent in 2010) (Suedostschweiz, 2015). A second remarkable anomaly before the scenarios start is the significant drop of amounts sold by both bundling organizations and traders in 2015. In January 2015, the exchange rate of CHF-EUR dropped by approximately 15% (cf. description of the scenario EUR). This immediately led to a massive reduction of amounts sold. In 2016 already, the amounts sold increased again, converging to the former level after several years.

Observing the various developments of the amounts sold by bundling organizations in the scenarios, the strongest rise of amounts sold can be observed in the EUR150-scenario, which is obviously a consequence of the increasing amounts of wood sold by forest owners. The same explanation applies for the DEC-scenario, where the amounts are slightly higher than in the BAU-scenario. The scenarios EUR080 and SET inter-

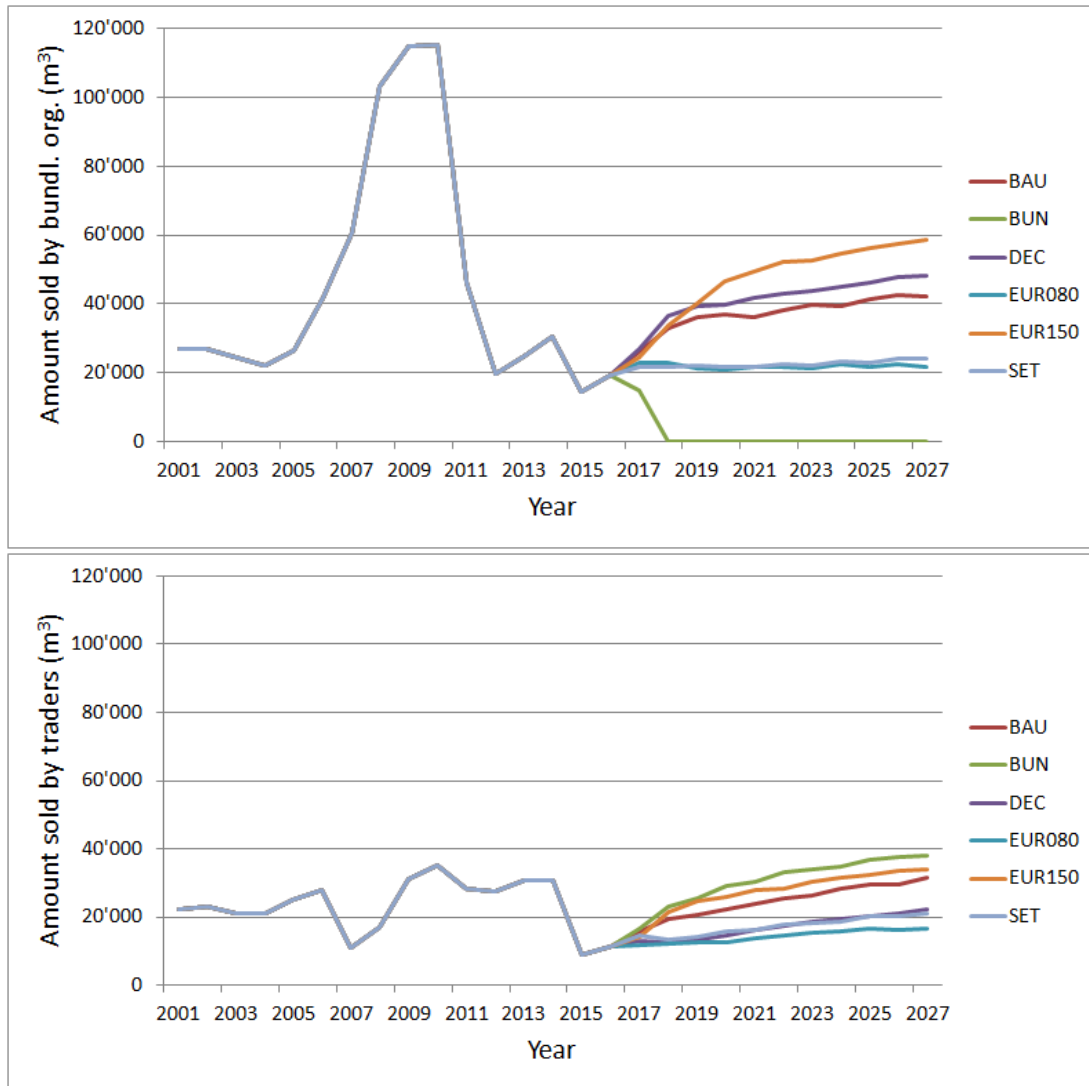


Figure 5.6: Amount of sawlogs sold by bundling organizations (top diagram) and traders (bottom diagram) in the different scenarios.

estingly lead to very similar amounts sold. This can be interpreted from a bundling organization's point of view that setting aside 39% of the public forests or a constant decrease of the exchange rate of 0.0288 CHF/EUR annually has the same consequences in terms of amounts sold.

Considering traders, the amounts sold rise in all the scenarios, as explained above. The intensity of the rise differs, particularly in the first years of the scenarios. In the BUN-scenario, the increase is the strongest as traders are now the only intermediaries in the market. The second strongest increase can be observed in the EUR150-scenario, followed by the BAU-scenario. The increases in the scenarios DEC and SET are much weaker and not considerably different from the EUR080-scenario.

There are two further remarkable observations. The first is the difference of amounts sold between bundling organizations and traders in the DEC-scenario in comparison to the respective BAU-scenario. Bundling organizations sell in the DEC-scenario more than in the BAU-scenario, traders sell less than in the BAU-scenario, which means that profit-oriented forest owners prefer bundling organizations over traders as intermediaries. The second observation is that the SET-scenario has the same consequences as the EUR080-scenario for bundling organizations, while for the traders, the consequences of set-asides are not as intense as the consequences of the EUR080-scenario. This can be explained by the strong link between bundling organization and forest owners, which results in bundling organizations being more affected by set-asides in comparison to traders.

5.3.2 Energy Wood

5.3.2.1 Prices

Figure 5.7 shows the prices paid for energy wood (softwood) by energy wood consumers in the study region under different scenarios. The thick black line shows the actual historical prices of energy wood from 2001 to 2016.

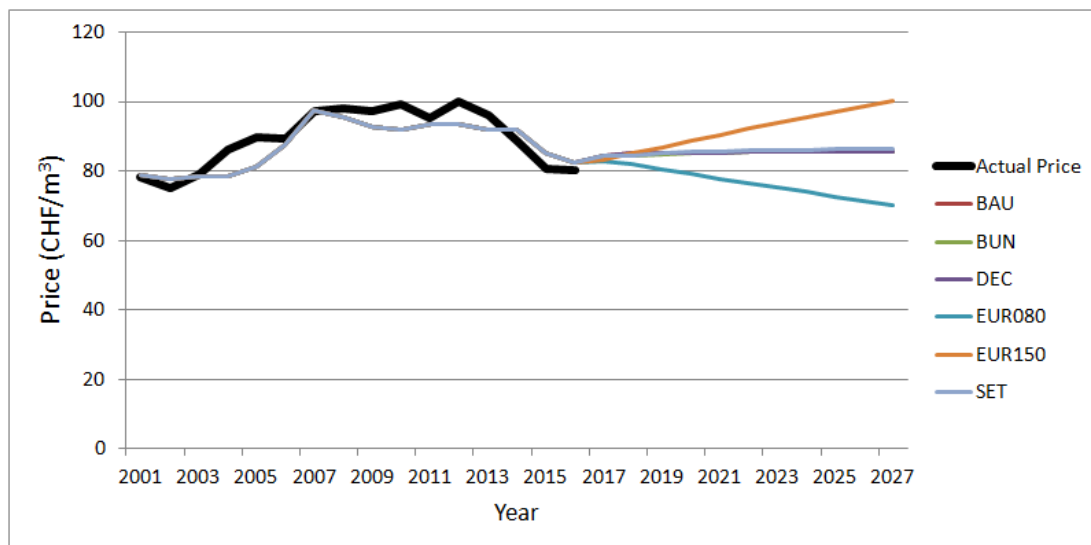


Figure 5.7: Prices paid for energy wood by energy wood consumers. The prices in the scenarios BAU, BUN, DEC, and SET are almost equal, and therefore overlap in the diagram.

The EUR-scenarios have a strong influence on the energy wood prices, while in other scenarios, the price development is almost equal. A very small difference can be observed in the SET-scenario, where prices in 2027 are approximately 1% higher than in the other scenarios. This can be explained by the reduction of supply, which leads to less competition.

The reason that the price development for the scenarios BAU, BUN, and DEC is almost equal, is that they mainly influence the sawlogs market. The DEC-scenario only changes the decision parameters of forest owners when they sell sawlogs as this is the main product which triggers the harvesting process. In the BUN-scenario, the provisions previously paid to the bundling organizations are now retained by the forest owners and not passed on to the customers, such as those in the sawlogs market.

5.3.2.2 Amounts

Figure 5.8 shows the amount of energy wood (softwood) sold by forest owners in the study region. The thick black line shows the actual historical values of *produced* energy wood from 2004 to 2016. The amounts of energy wood produced and sold are generally equalized in the long run. The small differences in the individual years can be explained by the time between harvesting and selling (energy wood can be stocked up to 2 years in the forest without loss of quality) and annual cut off.

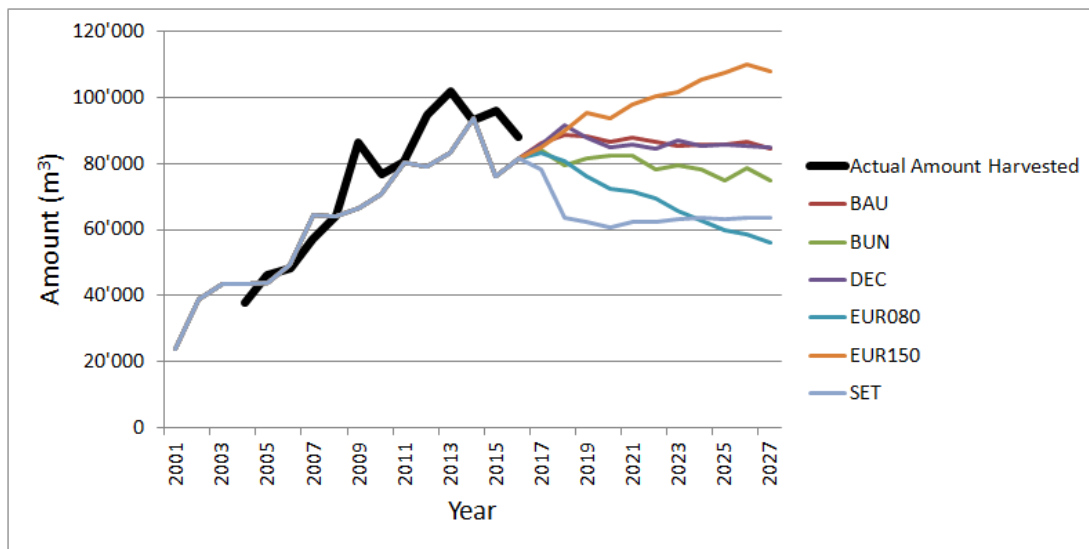


Figure 5.8: Amount of energy wood sold by forest owners.

The amount of energy wood sold in the scenarios BAU and DEC show almost equal and constant quantities in time. As previously explained for energy wood prices, the DEC-scenario only influences the decision parameters of forest owners selling *sawlogs*; therefore, there is no influence on the energy wood market.

In the two EUR-scenarios, the sold amounts rise/drop according to the prices of energy wood.

In the SET-scenario, the sold amounts first drop by almost the same percentage as the percentage of public forests that are set aside, before they start to rise again slightly. This can be explained by the price difference between sawlogs and energy wood. The prices of sawlogs slightly decrease in the scenarios BAU and SET, while the price for energy wood remains almost constant. This leads to a small shift of the percentage of a tree that is used for sawlogs and for energy wood, more toward energy wood.

In the BUN-scenario, forest owners sell approximately 10% less energy wood in comparison to the BAU-scenario. This can be interpreted as bundling organizations providing valuable support in finding demanders for energy wood.

5.3.2.3 Intermediaries

Figure 5.9 shows the amount of energy wood sold by intermediaries in the study region. For this data, the actual historical values are unknown. Until the scenarios start, the development of the variable is similar for bundling organizations and traders, with traders showing marginally higher amounts and more distinct peaks in comparison to bundling organizations. The amounts sold clearly increase until 2014 and show a short drop in 2015, when the exchange rate significantly dropped. This is in accordance with the amounts sold by forest owners in the study region, from which the intermediaries buy their wood.

After the start of the scenarios in 2017, the scenarios BAU and DEC show approximately constant quantities, both for bundling organizations and traders. The reasons for the similar developments of BAU and DEC concerning energy wood were mentioned above (section 5.3.2.2).

The BUN-scenario provides traders approximately 20% higher sales or 2000 m³ more in absolute terms. In 2017, before the bundling organizations disappeared, they sold approximately 8000 m³ annually. Therefore, traders were not able to overtake the complete amount from the other type of intermediary. This complies with the observation on the amount sold by forest owners in the BUN-scenario in Figure 5.8, where bundling organizations provide valuable support in finding demanders for energy wood, apparently much more than traders.

The EUR-scenarios have the same consequences for bundling organizations as for forest owners: sold amounts rise or fall similarly for both agent types. Traders profit much more from an increasing exchange rate, and even a decreasing exchange rate has only a low impact on the amount of energy wood sold by traders. This can be clarified by the following observations: when the exchange rate increases, almost all energy wood that is additionally sold by the forest owners goes to the traders who then export it, which explains the high increase in traders' sales. When the exchange rate decreases, the forest owners sell a higher percentage of their wood to traders, which explains why traders are less affected in this scenario in comparison to bundling organizations.

The SET-scenario has different effects for bundling organizations and for traders. For bundling organizations, the set-asides lead to a decrease in sales, similar to the EUR080-scenario; however, for the traders, this leads to an increase of sales of approximately 20%. Bundling organizations buy only from forest owners; therefore, they directly depend on the total size of managed forests. Traders profit from the set-asides and achieve an increase in energy wood sold. It can be observed that the remaining public forest managers proportionally sell less energy wood to bundling organizations and more to traders. The explanation for this is that due to the reduction of supply from public forests, bundling organizations are challenged to bundle sufficient amounts of energy wood, as there are less suppliers though the same number of bundling organizations.

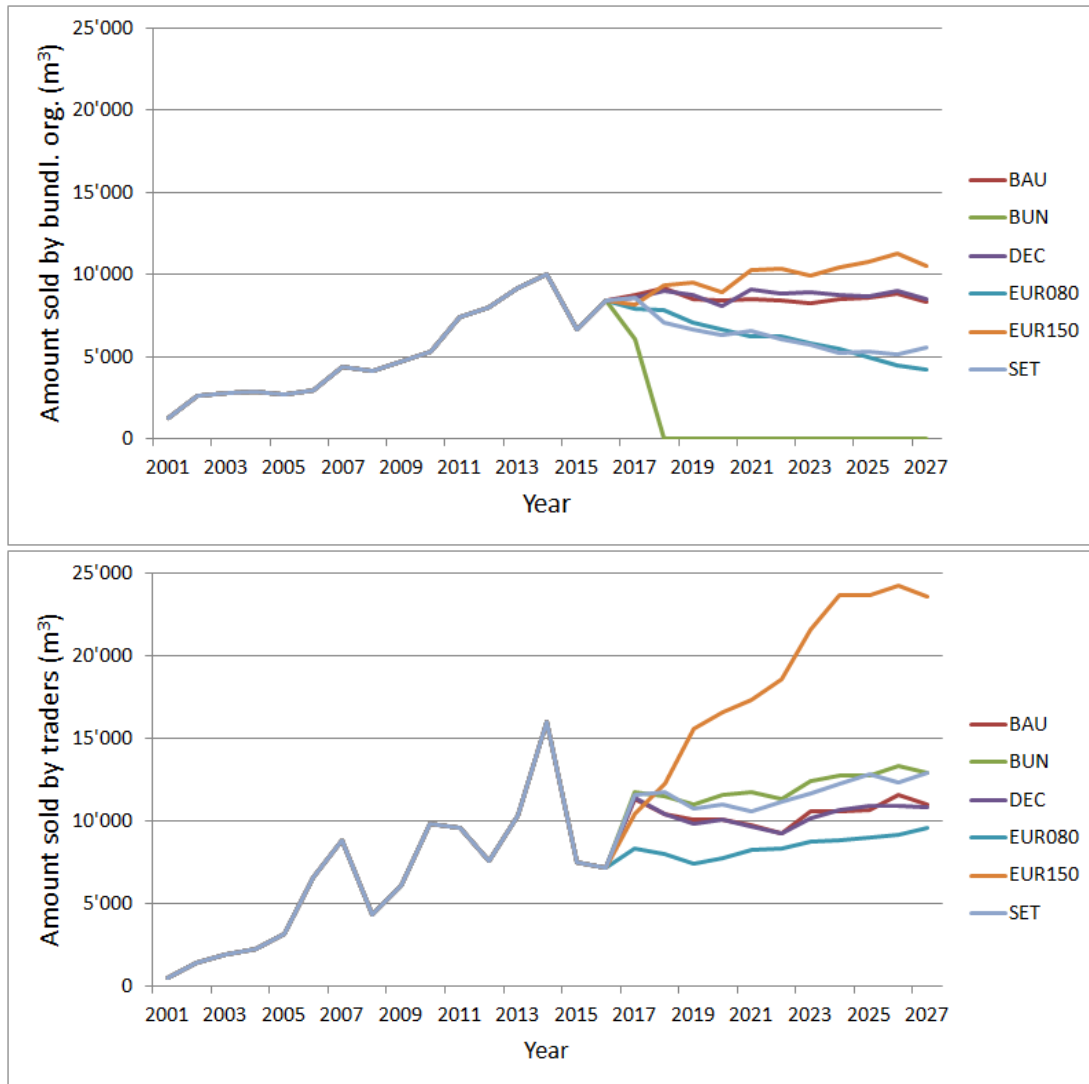


Figure 5.9: Amount of energy wood sold by bundling organizations (top diagram) and traders (bottom diagram) in the different scenarios.

Another interpretation would be that traders start to import wood to counterbalance the loss of domestic supply. Thoroughly analyzing the model output though reveals that import of energy wood is almost nonexistent. This can be explained by the relatively high transportation costs of energy wood and the fact that the domestic supply of energy wood even in this scenario is still sufficient to satisfy the domestic energy wood demanders.

5.3.3 Summary of Scenario Findings

In the previous sections, we presented the results of the scenario simulations by interpreting the various variables observed. In this section, we summarize these results by discussing them holistically, per scenario rather than per variable.

The BAU-scenario shows approximately constant values for most variables, except for the prices of sawlogs, which slightly decrease, and the amounts of sawlogs sold by intermediaries, which first strongly rise back to their level before the historical drop of the exchange rate and then continue with a slight but continuous increase. The slight decrease in prices can be explained by the fact that sawmills in the study region are disappearing over the years. These market exits have been occurring since several decades in the study region (BFS, 2013). The consequence is a reduction of demand which leads to lower prices. The continuous disappearing of sawmills also makes export more important as sawmills and exporters are the only demanders in the sawlogs market. This makes the intermediaries focus on delivering to exporters, which slightly shifts the market shares of exported wood from forest owners toward intermediaries.

The absence of bundling organizations in the BUN-scenario leads to slightly lower sawlogs prices, which reflects the absence of the provision previously taken by the bundling organizations. However, bundling organizations took the provision for a service, which forest owners now have to undertake themselves. Considering the energy wood market, forest owners have profited from this service, as without bundling organizations, they are unable to continue to sell the same amount of energy wood. Traders can profit in both the markets as they are now the only intermediaries in the markets.

The DEC-scenario only influences the sawlogs market: both prices and the amount sold by forest owners are approximately 3-4% higher in comparison to the BAU-scenario. The more profit-oriented forest owners in this scenario prefer bundling organizations over traders as intermediaries, which increases the amount sold by bundling organizations by 10%-15%, and decreases the amount sold by traders by approximately 30%.

The EUR-scenarios have a strong influence on all the variables observed. A higher exchange rate leads to higher prices and higher sales, while a lower exchange rate leads to lower prices and lower sales. However, the extent of increasing or decreasing sales is sometimes different: considering the energy wood market, traders profit more from an increasing exchange rate than bundling organizations, and they are also less affected by a decreasing exchange rate.

The SET-scenario, where 39% of the public forests are set aside, leads to slightly higher sawlogs prices (+2%). Considering sawlogs sales, it affects bundling organizations (-40% sales) more than traders (-30% sales) as bundling organizations buy their wood only directly from forest owners. Prices in the energy wood market are not affected. The amount of energy wood sold by forest owners and bundling organizations decreases, traders profit from that situation and sell 10-20% more.

5.4 Conclusions

We presented a model of the wood markets in a study region in Switzerland. The model, which was validated with empirical data from multiple sources (Holm et al., 2018), is adjustable regarding market structure, agent behavior, and policy interven-

tions. We simulated and analyzed several scenarios relevant to stakeholders and policy makers, and showed that the model delivers reasonable results that can be used to draw conclusions back to the real system.

While the model provides the exact numbers to certain questions, such as what is the rate at which the price of sawlogs changes if 39% of the public forests are set-aside, these numbers have to be interpreted with care before political decisions are made that will affect the real system. A careful interpretation includes explaining the results by analyzing causal mechanisms that lead to a change in an observed variable. It has to be checked which causal mechanisms are involved, and also which ones are not. It has to be evaluated if these causal mechanisms are realistic, and if the intensity of such mechanisms in the real world is similar to those in the model. Attention must be paid to not interpret the results by considering causal mechanisms that could exist in reality but are not actually modeled. For example, price fixing can explain some phenomena observed in the scenarios, but as there is no price fixing between agents in the model, this is not a causal mechanism that is allowed for the interpretation of the results (price fixing in fact plays a negligible role in the market modeled here, and was therefore omitted in the model). Finally, the accuracy of the assumptions for the BAU-scenario need to be judged as the size of the impact of a scenario depends on the baseline assumed in the BAU-scenario (cf. Hilty et al., 2014). Considering that these steps were thoroughly conducted, the model can be a helpful instrument to conduct experiments *in silico* and thereby identifying the consequences of discussed political measures prior to their implementation. The nature of agent-based models allows capturing of emerging phenomena, i.e. phenomena that result from the interaction of the agents, and that are often not obvious or even counterintuitive (Bonabeau, 2002). Therefore, we conclude that the presented model has a large potential to support planning of political measures concerning the wood markets under study.

5.5 Acknowledgements

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