Development, evaluation and application of inference-based decision support methods to meet the rising wood demands of the growing bio-economy sector

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Contents

List of Figures

List of Tables

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tbd: Abschließende Formatierung, sodass zu große Abstände verschwinden
Opt-Artikel: Newton-Raphson ist keine eindeutige Methode, sondern Gradient-Based
Nagel 1996 ist der älteste Artiel, den ich zu TreeGRoSS gefunden habe. Da hieß es allerdings noch NEWS. Würde gerne die erste Quelle zitieren.
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Summary

Summary.

Zusammenfassung

Zusammenfassung.

Chapter 1

Introduction

> *"Forest management, whether for timber production, biodiversity, or any other goals, requires decisions that are based on both our knowledge of the world and human values."*
>
> — Davis, Johnson, Bettinger, Howard, *Forest Management*

1.1 Theoretical background of decision making

Decision making is the last step in the process of planning, which starts with actually discovering the existence of a decision problem. The complexity of the planning process, is thereby determined by the type of decision and may vary from very simple daily decisions to extensive and long-lasting decision processes (Kangas et al., 2015, p. 3-4). Relatively easy and quick decisions differ fundamentally from more complex decisions in terms of problem structure, consequences, preferences of the decision-maker and solution evaluations (Keeney, 1982, p. 807-808). While everyday choices in a professional framework are usually based on associative selections and personal preferences, crucial decisions or decisions with long-lasting consequences are often taken analytically with explicit inference methods (Stanovich & West, 2000, p. 659, 672; Kangas et al., 2015, p. 3). These two different decision types, often called *systems* in behavioral sciences (e.g. Stanovich & West, 2000, p. 658), underlie significantly different theorems. Following classical theory of decision examination, decisions can be described either *descriptively* or *normatively* (Bitz, 2005, p. 6). Examining decisions from a descriptive perspective means the evaluation of individual and social actions. The descriptive decision theory analyses actual decisions with the aim of examining how decision-makers act in reality and how decision making actually works. Hence it analyses the principles descriptively without further investigation of the underlying purposes. Descriptive decision studies try to answer the question *how* but not *why* decision-makers decide (Simon, 1979, p. 499-501). Findings from descriptive studies, therefore, do not allow the drawing of conclusions about plausibility or reasonability. Lessons from empiric-descriptive analysis, though, do not necessarily lack reasonability. Descriptive decision theory does not inquire into the rationale behind decisions (Simon, 1979, p. 500). The objective of the normative decision theory is the examination of particular reasons behind decisions. Hence, in contrast to the descriptive theory, normative studies are evidence-based rather than descriptive. In particular, they aim to theoretically explain the causal network that leads to decisions. Normative decision models are usually computer-aided, mathematical, statistical or numerical computations trying to explain decision processes by accounting for their intrinsic criteria. If researchers or decision-makers are interested in the rationale behind fairly complex decision problems, a normative examination will usually be obligatory.

Normative decision examination constitutes the foundation of *operations research* (Shim et al., 2002, p. 112; Simon, 1979, p. 498), an interdisciplinary science with elements from statistics, mathematics, economics and computer sciences, which developed simultaneously with the first digital computers (Churchman et al., 1957). Operations research, also known as management sciences or decision sciences, is the science of building and using computer-aided models for decision support (Wacker, 1998, p. 373-374). Methods from operation research are nowadays mandatory tools for almost all crucial intermediate- and long-term decisions to be made in a professional framework. Operations research hence builds the theoretical background of all modern computer-aided programs for decision support, also called *decision support systems* (DSS). The main aim of DSS is to support complex decision problems by providing crucial theory or inference-based informations to decision makers. In one of the most popular definitions of DSS, in Gorry & Morton (1971, p. 26), it is stated that decision processes must be simplified and abstracted in a way that they can be programed as computer code. Type and intensity of the abstraction depend on the complexity of the decision problem. In this context, abstraction means the identification and simplification of relevant elements of a decision. Those elements can be theoretical or inference-based. A very simple and often used example to examine elements inference-based is the linear optimization. As one property of linear optimization is the assumption of linearity between decision variables and decision objective, application of linear optimization requires very strict simplifications (Kangas et al., 2015, p. 129). A linear regression analysis is one possibility to force all crucial decision elements into a linear framework, thereby fulfilling the property of linear optimization. Prior to implementation of a linear optimization, as an example for a DSS, a linear regression analysis can hence be used as a tool to simplify the decision elements. The abstraction and simplification of decision processes into *programmable* elements is usually performed using statistical inference, such as regression or variance analysis. Applied statistical models are therefore mandatory tools right from the beginning of operations research (Churchman et al., 1957). All further decision elements, in particular elements that are unstructured or far too complex to simplify them with statistical methods, are called *non-programmable* decision elements. Those elements cannot be considered in a DSS. Prior to implementation into computer-aided models, decision-relevant aspects must be gathered, reviewed and simplified. A complete and accurate normative decision analysis is, therefore, a prerequisite for the development of a DSS. Almost all modern decision support models are based on classical decision theory, as they basically translate normative inquiry into applicable models for scientists, practitioners or any other decision maker. Next to the actual variables and rules, typical DSS also have a user front-end and a data-warehouse (Hansen, 2012, p. 2; Shim et al., 2002, p. 115). The user front-end facilitates the application of a DSS for the user. The data-warehouse enables storage of necessary input data and the solution.

1.2 Decision support systems in forest planning

Decisions in forest management never affect particular issues in isolation. Once made, management decisions in forestry will impact on many economic, ecological and social issues. A challenge foresters typically have to cope with is the long-term consequence of their operations. Daily operational decisions of foresters, such as harvesting at the stand level or planting, usually have very long lasting consequences. Foresters must, therefore, review the consequences of their decisions very thoroughly. Forests should be managed in such a way that they produce income for the forest owner on the one hand, while at the same time following conservation and recreational issues on the other hand (Kangas et al., 2015, p. 11; Möhring, 1997, p. 67). Simultaneous fulfillment of all three functions, the ecological, economic and social functions - on the entire forest land is the guiding principle of multifunctional forestry in Germany. It is firmly anchored in the Federal Forest Law in Germany (Möller, 2007, p. 457). The concept of *sustainability* plays a central role in forestry. In one of its most recent and general definitions, sustainability means the development of forests such that current and future generations can benefit from all three forest functions (United Nations General Assembly, 2005, p. 14; see also Kangas et al., 2015, p. 14). As a consequence, forest management decisions may not lead to a decline in several aspects, such as *biodiversity*, *productivity* and *regeneration capacity vitality* (Ministerial Conference on the Protection of Forests in Europe, cited from Kangas et al., 2015, p. 15). Forest management thus requires careful planning, considering multiple criteria at the same time. Owing to this high complexity, crucial decisions in practical forestry are rarely made by single persons. Operational forest decisions are usually based on a complex synthesis of intermediate-term plans and long-term strategies that enable long-term issues, such as general forest development or nature conservation issues, to be taken into account in practical daily operations. Daily operational forest decisions made by foresters, e.g. harvesting or planting on stand level, normally rely on intermediate-term management guidelines that are created for periods between 5 and 20 years (Kangas et al., 2015, p. 12). The German intermediate-term forest management planning is, especially in the public forests, a long-established, continuously improved process which tries to implement a strategic orientation into spatially and temporally explicit guidelines for operational decision makers (Böckmann, 2004, p. 156-158). The entire forest planning process is, hence, a complex framework that is comprised of long-, intermediate- and short-term management plans with the aim of supporting the operational decisions of foresters with respect to a wide range of relevant issues.

Next to an increasing demand for wood as raw materials (Mantau, 2012, p. 8), requirements on conservation and recreational issues are rising as well. For example, Germany's national strategy for biological diversity has the goal of natural development on 10 % of public owned and 5 % of private owned forest land (BMU, 2007, p. 45). As a consequence, more than 700,000 hectares of forest land are planned to be set-aside by 2020 (TI, 2014). Auer et al. (2016, p. 3) calculated the wood potential, particularly for European beech, in the center of Germany. They concluded that the potential was already almost completely exhausted in the period between 2002 and 2012. An ongoing increase in wood demand coupled with a decrease in the available productive area and a simultaneous increase in recreational issues (Hansen, 2012, p. 1), while still maintaining positive returns, poses new challenges for forestry and the entire wood sector. The degree of complexity in forest planning is thus expected to increase even further.

This development explains the need for detailed, rational decision support (Hansen & Nagel, 2014, p. 2). If demand further rises, innovative computer-aided supply chains, as well as processing schemes, become even more mandatory in order to serve all wood consumers properly. DSS can be useful tools to simplify the complex framework of forestry decisions. They help by structuring the highly complex forest decision problems into smaller, solvable sub-problems. The advantages of DSS for forestry purposes were already discovered in the early 1980s (Reynolds et al., 2008, p. 499). Nowadays, numerous examples of useful DSS can be found in forest practice and forest sciences covering a very broad range of purposes. Some very simple forest DSS are, for example, the *generalized maximin method* or the *certainty equivalent method* (Kangas et al., 2015, p. 25, 28). Complex inference based decision support tools like the WaldPlaner (Hansen & Nagel, 2014) have already become relevant in the practical intermediate-term forest planning, e.g. in Lower Saxony (Böckmann, 2004, p. 158). *WaldPlaner* is a DSS for practitioners and scientists with a user friendly interface that combines a data-warehouse with the long-established and widely used tree growth and yield simulation software *Tree Growth Open Source Software* (TreeGrOSS) (Hansen & Nagel, 2014, p. 46; Nagel, 2009). It enables, for instance, growth and yield simulation of multiple forest stands. It offers foresters the opportunity to review the consequences of management decisions and hence supports sophisticated evaluation of forestry decisions. Computer-aided forest simulation software in general have great potential to improve the effectiveness and accuracy of forest planning (Davis et al., 2001, p. 210). They are superior to classical yield-tables since they can consider many more relevant aspects for growth and yield, such as species mixtures, complex within-stand structures and competition, as well as specific growth and treatment rules (Hansen, 2012, p. 3 Muys et al., 2010, p. 93).

1.3 Optimization of forest planning

Right from the beginning of the use of DSS in forestry, optimization techniques came into use (Kangas et al., 2015, p. 16). As optimization procedures were initially developed for efficient allocation of finite resources (Davis et al., 2001, p. 271), they are suited to many decision problems in forestry, a field with naturally scarce resources. Combinations of modern growth and yield simulation software and optimization procedures are currently the focus of forestry research. A simultaneous application of growth simulators and optimization procedures offers opportunities for forest planning, as it enables foresters to consider environmental circumstances which change over a longer timeframe (such as climate change or nitrogen deposition) in their operational short-term decisions (Möhring, 2010, p. 346-347; Pretzsch et al., 2008, p. 1081). A recent example from forest sciences can be found in Yousefpour & Hanewinkel (2009). They developed an approach to optimize thinning operations in terms of economic return, which also takes timber production, carbon storage and biodiversity constraints into account. They combine the growth and yield simulation software TreeGrOSS with the *dynamic linear programming* optimization procedure. They used an integrated simulation-optimization approach to estimate the monetary drawback of different treatment and nature conservation scenarios. Combined simulation-optimization methods are not novel in forestry. The United States Forest Service, for example, has applied such combined methods in practical forest planning since the 1980s (Hoganson & Meyer, 2015, p. 33). Other countries also have experience in the practical application of combined methods. Recently combined methods have found practical use in, for instance, the USA and Finland (Hoganson & Meyer, 2015, p. 41). Since both growth and yield simulation models, as well as optimization methods, have developed considerably in the last decade, modern combined methods have the potential to solve more sophisticated decision problems in forestry (Kangas et al., 2015, p. 16-17; Muys et al., 2010, p. 93).

1.4 The role of bio-economy in forestry

Bio-economy is defined as a combination of all economic sectors that refine biological resources by physical, chemical and biotechnological processes (de Besi & McCormick, 2015, p. 10462). The bio-economy itself is no novel sector but an aggregation of formerly separately regarded sectors, which are all based on biomass as a major resource. The main advantages of bio-economy as an aggregated sector are the research cooperation of formerly distinct companies in order to benefit from synergy (Auer et al., 2016, p. 1), as well as commonly evaluated supply chains and resource demands (Geldermann et al., 2016, p. 3).

With an overall turnover of 2 trillion € in 2014, including resources from agriculture, forestry and fishery, the European Union's bio-economy sector leads in a worldwide comparison (El-Chichakli et al., 2016, p. 221, 223), with Germany playing a particularly important role (Hennig et al., 2016, p. 200). Although the share of forestry itself as a primary producer only amounts to 2 % (35 billion €), forestry currently plays a crucial role for resource supply in the bio- economy sector. The bio-based sector is a factor of considerable importance in Germany's national economy as well. The bio-based economy, including primary production as well as manufacturing and services, accounted for approximately 8 % of Germany's gross value-added in 2007 (Efken et al., 2012, p. 29-30). Innovative bio-based products have potential as substitutes for end- and semi-finished products that are traditionally based on fossil resources. In the national bio-economy strategy, the German Government therefore decided to strengthen the bio-based sector until 2030 (BMEL, 2014b, p. 15-16). Novel production methods could enhance the significance of forest biomass (in particular of small dimensioned wood) for use in bio-refineries. Ekman et al. (2013, p. 49) revealed woody biomass to have great potential for chemical semi-finished products. Regarding the political and economic circumstances, the importance of the bio-economy sector in general, and in particular of forestry, is thus expected to increase further. The demand for wood is high and steadily rising. From a forestry perspective, the question arises, whether prospective demands for woody biomass can still be served with the available resources.

Cooperation between wood processing companies provides advantages, particularly for forest enterprises, with respect to improving planning possibilities. If the supply chains of formerly distinct smaller companies are joined together to an integrated super-regional supply chain which includes interactions between companies, logistical planning for forest enterprises will be considerably simplified (Geldermann et al., 2016, p. 3). Supplying to well-prepared, centrally controlled networks can be beneficial in terms of increasing planning reliability and reducing planning costs, as communication between decision makers in bio-economy and forestry will be structured and therefore facilitated.

Modern modeling techniques already enable reliable forecasting of wood potential from forests. With help of DSS, forecasting of the expected wood potential is already frequently applied in the context of cluster studies (e.g. BMEL, 2016), scientific studies (e.g. chapter 2) and intermediate-term forest planning (e.g. Böckmann, 2004). Wood supply can already be forecast reliably for time horizons up to 20 years. Sound knowledge of the respective wood demand will therefore have a considerable positive effect on intermediate-term forest planning. For similar reasons bio-economy DSS can provide useful tools for the assessment of wood demands. One aim of the collaborative bio-economy sector is the development of such super-regional and interactive DSS (Ollikainen, 2014, p. 362). From the perspective of forestry, the collaboration of wood processing companies is desirable, since it will increase the reliability of wood demand studies. A common forecast of wood demand from a network of joined companies offers advantages, as it enables reliable matching of the forecast wood potential with prospective demand. Valid information on the required resources of wood processing networks can improve planning security, benefiting both bio-economy companies as well as forest enterprises.

Innovative bio-economy companies, such as bio-refineries, need a continuous wood supply to ensure ongoing manufacturing process (Ollikainen, 2014, p. 362). Their success crucially depends on delivery contracts which ensure continuous wood supply. This meets the requirements of the forest sector, as delivery contracts can be beneficial for forest enterprises as well. Delivery contracts facilitate intermediate-term planning for both sides. Contractually determined continuous wood supply, on the other hand, leads to a limitation of the forest treatment possibilities. It restricts the possible harvesting operations. Wood usage ahead of the standard treatment schedule, as it is sometimes necessary to fulfill contractually determined minimum wood delivery amounts, can lead to usages exceeding growth in specific forest stands. To meet the concept of sustainability, however, each utilization above the growth must necessarily lead to reduced utilization at another time point (Möhring, 1997, p. 67). The forester can thus be forced to harvest stands at unfavorable time points. This reduces the options of stand treatment within a forest enterprise (Möhring, 2010, p. 351-352). As introduced in section 1.2, the intermediate-term action plan represents the most favorable forest development schedule under a given strategic orientation of the forest enterprise. If all guidelines are respected properly, the standard treatment therefore represents the maximal harvestable wood volume without violating the intrinsic strategy of the forest enterprise. Any distortion will lead to a deviation from the preferred forest development. The difference in harvestable wood potential between the unrestricted treatment and the treatment under delivery restriction can be interpreted as the opportunity cost of the delivery contract (Möhring, 2010, p. 353). It is thus the price that a forest enterprise has to pay for the benefits of delivery contracts.

1.5 Aim of the thesis

Biomass from forests has the potential to provide a largely carbon-neutral supply of material to the bio-based sector and could therefore make a significant contribution to a clean bio-based industry. Modern utilization techniques enable the substitution of fossil resources by renewable biological resources. In this context, the bio-economy contributes to reducing the dependency upon fossil raw material and thus to the reduction of carbon dioxide emissions (Ingrao et al., 2016, p. 4). Dedicated political programs and comprehensive research projects have strengthened the development of the bio-economy sector worldwide and show its current and prospective importance. The increasing political, social and economic importance of the bio-economy (e.g. BMEL, 2014b, p. 15-16) reveals a worldwide process of rethinking towards a cleaner production.

The forest sector, as an important primary producer of renewable resources for the bio-economy, plays an important role for the success of the bio-economy. The rising demand for wood, however, could exceed the sustainable achievable wood potential of specific assortments. Reasonable distribution of the scarce resources is, therefore, a major challenge, which the forest sector has to face. In times of simultaneously rising demands on all three forest functions, the main challenge is *"How to match the resource demands of a rising bio-economy sector with the available wood potential without compromising the concept of sustainability?"*

I present differentiated applied statistical analyses which strengthen distinct decisions in the wood supply chain of the bio-economy. I will introduce a descriptive analysis to calculate an overview of available wood potential in an important supply region and distinct normative inquiries investigating the decision elements of three relevant decision problems for supply of the bio-economy sector.

1.6 Structure of the thesis

After the general introduction, I present distinct essays which deal with the research questions and problems mentioned in the introduction. Chapter 6 completes the thesis with a general discussion of all four studies.

1.6.1 Analyzing status and development of raw wood availability in the European beech-dominated central Germany

The initial step of a planning process is the actual identification of a decision problem (section 1.1). Prior to calculation of methods to overcome resource distribution problems, the existence of a resource scarcity must be examined. If resources are not scarce, there will be no resource distribution problem. Availability above a particular demand will result in an oversupply. Supplying all market participants with desired raw material would be trivial in such a scenario. The first reasonable step to tackle a resource distribution problem is hence an estimation of the actual availability and demand of the respective resource.

The first approach to answer the research question is a cluster study to analyze the available wood potential and the market situation in a possible wood supply region for the bio-economy in Germany. The current and future availability of European beech (*Fagus sylvatica* [L.]) raw wood, one of the most important wood resources for the growing bio-economy sector (Auer et al., 2016, p. 16), was investigated in the beech-dominated center of Germany. Chapter 2 shows the results of a study analyzing the German federal states of Lower Saxony, North Rhine-Westphalia, Hesse, Saxony- Anhalt and Thuringia in terms of their beech wood potentials and demands.

The potential raw material within this supply region was calculated using the publicly available database of the German National Forest Inventory. These data were advantageous, since they represent a high-resolution systematic grid of sample points over the whole supply region and consider all ownership types (Schmitz et al., 2008). The future wood potential was then forecast using the forest DSS WaldPlaner (Hansen & Nagel, 2014).

The study is an example of how inventory data extrapolation and forest simulation methods can be applied to create a quantitative base to support the strategic orientation of the bio-economy sector. Profound wood potential analysis on current and predicted wood amounts can provide valuable information for upcoming and established companies and help in appraising raw material availability for prospective production.

1.6.2 Biomass functions and nutrient contents of European beech, oak, sycamore maple and ash and their meaning for the biomass supply chain

Modern utilization techniques in the fields of bio-economy are able to make use of smaller dimensioned wood of, in particular, broadleaf species. Because the chemical constituents of the wood are dissolved in innovative bio-refineries, novel bio-economy companies are mainly interested in the dry woody biomass, rather than in the dimension or form of the wood assortments ((Ekman et al., 2013)). These novel companies are thus interesting from the point of view of forest enterprises, as the smaller wood residuals left after harvesting the stem wood presently often remain in the forest.

The usage of small dimensioned branches is, however, controversial. Too high nutrient exports lead to soil degradation and are therefore not compatible with the concept of sustainability (Pretzsch et al., 2014, p. 261). Biomass functions and nutrient contents are useful tools for estimating the acceptable degree of harvesting intensity.

Biomass functions have two advantages for the bio-based sector. They can help in exploiting the available wood potential, in particular for small wood and they can support decisions on the raw material supply chain. They enable estimation of single tree dry biomass via easily measurable tree attributes and therefore allow valuation of the biomass flow in the supply chain. The potential of forest sites can only be entirely exploited when the avoidance of soil exhaustion is also taken into account. For this, the estimation accuracy of the site-specific wood potential can be improved by using realistic biomass functions and nutrient contents. Biomass functions and nutrient contents are available for European beech and oak (*Quercus robur* [L.] and *Quercus petraea* [Matt.]) but not for sycamore maple (*Acer pseudoplatanus* [L.]) and ash (*Fraxinus excelsior* [L.], which often occur in mixture with beech (TI, 2014). Accurate biomass functions and nutrient contents for these species can thus help to unlock additional wood potential for the bio-economy that was, due to the lack of a basis for the calculation of compatible harvesting intensity, so far unused.

In chapter chapter 3, biomass functions and nutrient contents for European beech, oak, sycamore maple and ash are introduced. Their meanings for the supply of a bio-based industry with woody biomass are discussed in detail. The biomass and nutrient content models can then be used for the implementation into DSS, such as the WaldPlaner (Hansen & Nagel, 2014), in order to enable quick calculations of the site-specific wood potential and to calculate material flows of woody biomass.

It is shown how inventory methods for natural resources can be used to efficiently estimate the biomass of single trees. Generalized linear and nonlinear regressions were used to calculate biomass functions and nutrient contents for beech, oak, sycamore maple and ash. How multicollinearity problems in biomass measurements influence the estimate and the variance of nonlinear biomass models is empirically determined and discussed.

1.6.3 Modelling the economically viable wood in the crown of European beech trees

Even if the site specific ideal harvesting intensity is acknowledged to be valid, the economic viability of this wood potential may not be given. In chapter 4, a program to predict the economically viable wood of European beech crowns is presented.

The model, which is able to distinguish economically viable from unviable branches in the crowns of European beech trees, was programmed to calculate the maximal single-tree wood potential with respect to economic objectives. It therefore helps to enable full exploitation of the timber potential on the single tree level. It is the first model in scientific forestry literature that predicts the wood volume in European beech crowns with respect to the complex sympodial crown structure. It has advantages over available models, as it is not based on taper models but on actual morphological measurements. The model was performed on 163 European beech trees to calculate their individual economically viable wood volume. By performing regression analysis, the model results were used to develop a regression formula able to predict the economically viable wood volume in the crown.

The regression formulas were developed such that they can easily be implemented into DSS. They offer opportunities for the decision makers to assess the full wood potential from an economic perspective. The evidence-based prediction of the full tree-specific wood potential has two main advantages. The prediction of the actual harvestable wood volume is facilitated by the models. Prior to harvesting, foresters can use the model to easily estimate the processing intensity for optimal monetary return. They can thus assess the full wood potential of every harvesting operation. This enables the gathering of formerly unused wood volume and hence increases the wood potential for the bio-economy sector. The predictive model promises further advantages for operational planning. As accuracy of predicting the harvestable wood is enhanced, the viability of entire wood volume or biomass supply chains can be strengthened.

The estimation model of viable wood volume in European beech trees is basically an integration of a break-even analysis into the predictor of the multistage randomized branch sampling method. It is a combination of a biometric sampling strategy for single tree attributes (Gregoire & Valentine, 2008, p. 405) with an econometric critical value analysis (Mußhoff & Hirschauer, 2013, p. 46). Generalized linear and nonlinear regression, cluster analysis and linear discriminant analysis are used to parameterize applicable formulas for implementation into DSS.

1.6.4 Flexible Global Optimization with Simulated-Annealing

Although optimization procedures are already important planning tools in an international framework (Hoganson & Meyer, 2015, p. 1) and have shown their potential to support operational planning, while simultaneously considering long-term issues of (Hoganson & Meyer, 2015, p. 1; Pretzsch et al., 2008, p. 1081), they have so far only played a minor role in Germany. Steadily increasing demands for wood, as well as for further ecosystem benefits, makes forest harvesting planning in Germany increasingly more complex (section 1.2). For this reason, combined simulation-optimization DSS could be a promising tool for German foresters and forest scientists to support harvesting operations decisions in terms of intensity and time. Having a closer look at optimization methods seems, therefore, to be worthwhile. In chapter 5, a combined simulation-optimization DSS for support of intermediate-term forest harvesting planning is introduced, which is specifically adopted to German characteristics. Optimization of forest growth and yield is very complex and therefore makes high demand on the optimization procedure. The essay preliminary deals with the opportunities and limitations of different optimization procedures for use in forestry decision support. Finally, I present an optimization procedure, which is able to tackle the complex output of forest simulation software. An explicit example is then developed. The software enables calculation of the optimal thinning intensity in time horizons of up to 20 years, and takes sustainability and the strategic orientation of a forest enterprise into account.

The presented optimization procedure is part of a simulation-optimization software, which is currently comprised of four basic elements (Figure 1.1). The first element is the growth simulation, which performs the actual growth and yield simulations. Tree growth and yield are simulated using TreeGrOSS, a long established single-tree based simulation software of the Northwest German Research Institute. TreeGroSS is also the back-end of the widely used forest DSS WaldPlaner (Hansen & Nagel, 2014, p. 6-7). The growth and yield simulation element is a stand-alone Java written software, developed by Nagel (1996). The TreeGrOSS packages, formerly known as NEWS, are advantageous for an integrated simulation-combination system, since they are one of the oldest and most often used growth and yield software in Germany. TreeGrOSS is compatible with a variety of data-bases (Hansen & Nagel, 2014, p. 55) that can serve as the data-warehouse for storing the raw data and the results of the simulations.

The interface (Figure 1.1) links the simulation with the optimization module. It has the job of translating the TreeGrOSS in- and output into state and parameter spaces that are interpretable by the optimization software. The interface is an R written function that internally calls the growth and yield modules of TreeGrOSS. The function can be called in any R session and thus allows TreeGrOSS based growth and yield simulations to be run directly from R. *R* is a flexible statistical programing language allowing relatively easy implementation and manipulation of optimization procedures and additional features(Nash et al., 2014, p. 11-12). The interface thus enables easy connection between TreeGrOSS and many optimization libraries.

In TreeGroSS, harvesting intensity is specified by the difference between actual and user definable target basal area (Hansen & Nagel, 2014, p. 149-150). The interface function translates

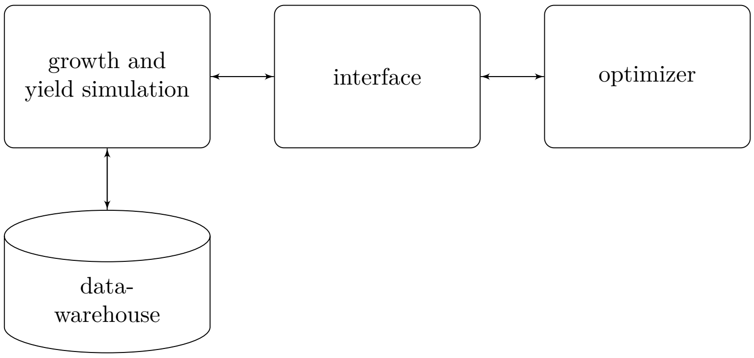

Figure 1.1: The four basic elements of the combined simulation-optimization software.

all target basal areas of all forest stands n_{stands} and all simulated years n_{years} of an optimization problem into a matrix with numeric values. The resulting objective matrix, which can be passed to the interface function, is thus of dimension n_{stand} x n_{years}, where n_{years} can also describe discrete steps of more than one year. Within the interface function, the values from the objective matrix are translated into TreeGrOSS interpretable goal basal areas. After translation, the interface function internally calls the growth and yield libraries basing on those entries. The resulting harvesting wood volumes from the TreeGrOSS simulation are stored and further processed in the interface function. The volumes are rated in terms of costs and revenues, summed and finally returned. The interface function is, in principle, a function that enables manipulation of the crucial TreeGrOSS simulation settings from R.

One of the most interesting and most challenging properties of forest planning optimization is the comprehensive and straightforward definition of the sustainability principle (Kangas et al., 2015, p. 15). Simulation-optimization DSS enable the objectifying of the principle of sustainability as explicitly defined computer rules. To consider sustainability in the optimization algorithm, I implemented two restrictions in the interface. In the last simulated year, the total standing volume (the sum of the standing volumes in all stands) is not allowed to be lower than a predefined limit. Additionally, each distinct standing volume in the last simulated year must be above a distinct stand-specific minimum limit standing volume. The predefined limits are based on growth and yield simulations under standard treatment circumstances. The interface function simply returns no valid value (`NA`), when a simulation result is outside the restriction limits. Besides the maximal harvesting volumes, which are determined by sustainability limitations, the interface also enables the definition of minimum harvesting volumes in the form of a further user selectable restriction. The optimization model hence enables definition of user defined annual minimum harvesting volumes for four assortments. The user can separately parameterize minimum annual harvesting volumes for deciduous and coniferous stem and industrial wood.

To conclude, the combined simulation-optimization introduced here, is based on sequential TreeGrOSS simulations with iteratively changing thinning intensity settings. Every iteration in the optimization progress is comprised of a TreeGrOSS simulation and rating of the harvested wood volume. As the TreeGrOSS packages are a complex causal network of rules, linear and nonlinear equations, the interface returns an irregular response pattern, including undefined parts. These properties make high demands on the optimization method. Many simpler functions are not suitable for the highly complex state space of the optimization problem. Extensive analyses of prospective optimization algorithms, including linear programming, direct-search and random-search heuristics, revealed the need for flexible heuristic optimization techniques to solve the problem. A very flexible optimization method without many assumptions on the loss function is presented and applied exemplary in chapter 5.

The combined model is an example of how applied statistical modeling can be used to strengthen the intermediate-term forest planning in times of a growing bio-economy sector. It offers an opportunity to optimize the intensity of harvest operations, thus enlarging harvestable wood potential for the bio-economy, without violating sustainability and enterprise-intrinsic strategic orientations. The combined simulation-optimization model provides a means to evaluate whether annual continuous delivery contracts are actual feasible without violating sustainability principles. With regard to the research question, the simulation-optimization model can be used to examine whether forest enterprises are able to comply with delivery contracts, keeping in mind their specific tree structures and intrinsic strategies. It will thus enable a sophisticated analysis of the ability of a forest enterprise to match the demands of the bio-economy.

It even allows further examination of the impact of delivery contracts. In a formal optimization framework, delivery contracts are restrictions that limit the possibilities of stand developments. Binding restrictions will necessarily have negative effects on the objective. This means, that the total harvestable volume in the time period of the optimization is either unaffected or decreased by delivery contracts with minimum annual wood amounts. Next to the benefits for forestry and bio-economy companies, delivery contracts also have opportunity costs for the forest enterprise (see also section 1.4). The simulation-optimization model makes calculating those opportunity costs possible by comparing the actual optimal treatment with the restricted optimum. It can, therefore, be a useful tool for assessing the advantages and drawbacks of continuous wood delivery rates from the perspective of forest enterprises. This information can be used to find an objective trade-off between the costs and the benefits of annual wood delivery quantity.

Kapitel 2

Mittelfristigem Anstieg folgt stetiger Rückgang - Zustand und Entwicklung der Rohholzverfügbarkeit in der buchenreichen Mitte Deutschlands

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- Veronika Auer, Hieronymus Bischoff und Matthias Zscheile begutachteten das Manuskript im Hinblick auf die Logistik.
- Ingrid Beitzen-Heineke, Hieronymus Bischoff und Wolf-Georg Fehrensen führten die Befragung der holzverarbeitenden Industrie durch, um die Rohstoffnachfrage in der Projektregion einzuschätzen.
- Ingrid Beitzen-Heineke, Jürgen Nagel, Holger Pflüger-Grone und Hermann Spellmann begutachteten das Manuskript mit Blick auf forstliche Sachverhalte.
- Christoph Fischer unterstützte die BWI Berechnungen.

2.1 Einleitung

Die Möglichkeit einer langfristigen, kontinuierlichen Holzrohstoffversorgung der Bioökonomie-Clusterregion Halle-Leuna wurde im Verbundprojekt *Plan C* (Perspektiven einer zukunftssicheren Logistik angewandt auf die natürliche Rohstoffversorgung in der Clusterregion, Förderkennziffer: 031A294 A bis H) im *Spitzencluster BioEconomy* des Bundesministeriums für Bildung und Forschung analysiert. Im Rahmen dieses Projektes wurde die buchenreiche Mitte Deutschlands als wichtigste Quelle für die nationale Buchenrohholzversorgung in Bezug auf ihre Rohstoffpotenziale untersucht und Konzepte für eine planbare Buchenholzbereitstellung erarbeitet. Beteiligte Projektpartner waren die Knauf Deutsche Gipswerke AG, die Georg Fehrensen GmbH, die Holzindustrie Templin GmbH, die DB Schenker Nieten GmbH, die Bruno Reimann GmbH & Co. KG, die Eickelmann Transport + Logistik GmbH, die Niedersächsischen Landesforsten, die Landesforsten Thüringen, der Landesbetrieb Hessen-Forst, die Otto-von-Guericke-Universität Magdeburg und die Nordwestdeutsche Forstliche Versuchsanstalt.

Derzeit sind ca. 15 % der Gesamtwaldfläche Deutschlands mit Rotbuchenbeständen (*Fagus sylvatica* [L.]) bestockt (BMEL, 2014a; TI, 2014). Da sich die Landesforstbetriebe zu einer langfristigen, naturnahen Waldbewirtschaftung verpflichtet haben (ML, 2014) und dies auch den waldpolitischen Zielen der Bundesregierung entspricht (BMEL, 2011), wird der Anteil von Misch- und Laubwald, insbesondere von Buchenwäldern, in Zukunft weiter zunehmen. Die ökonomische Bedeutung der Buche für Waldbesitzer und die deutsche Holzindustrie wird demnach stetig ansteigen.

2.2 Methodik

Das Untersuchungsgebiet umfasste Teile der Bundesländer Niedersachsen, Nordrhein-Westfalen, Hessen, Sachsen-Anhalt und Thüringen. Es erstreckte sich vom Niedersächsischen Bergland bis zum Taunus und dem Zentralen Hessischen Spessart, wobei der fichtendominierte Oberharz nicht berücksichtigt wurde. In westöstlicher Ausdehnung verlief die Projektregion von Ostwestfalen bis zur Leipziger-Sandlöss-Ebene.

Datenbasis für die Ermittlung des Holzaufkommens war die 3. Bundeswaldinventur (BWI 3). Hierbei handelt es sich um eine deutschlandweite Großrauminventur mit festen Stichprobepunkten (Traktecken), welche zuletzt zum Stichjahr 2012 durchgeführt wurde. Die Bundeswaldinventur hat neben ihrer Aktualität den Vorteil, dass der Stichprobenumfang in Bezug auf die Fragestellung in der gesamten Projektregion hinreichend groß ist (5039 Waldecken im Projektgebiet) und dass alle Waldbesitzarten berücksichtigt sind (ML, 2014). In Anlehnung an Schmitz et al. (2008) wurden Hochrechnungsalgorithmen für die Datenauswertungssoftware *R* (R Core Team, 2016) entwickelt und eine spezifische Auswertung des Waldzustandes und der Waldentwicklung der Projektregion auf Basis der BWI durchgeführt. Folgende Zielmerkmale wurden für das Untersuchungsgebiet berechnet: Waldfläche, Baumartenfläche, Vorräte sowie Holzzuwachs und Holznutzung und Flächenübergänge in der zehnjährigen Periode zwischen BWI 2 (Stichjahr 2002) und BWI 3.

Um das Buchenrohholzaufkommen mit dem Verbrauch der Holzindustrie in Relation zu bringen, wurden der Rohholzbedarf der 42 größten Buchenholzabnehmer aus der Region sowie des internationalen Exports eingeschätzt. Datengrundlage bildete eine Befragung der holzverarbeitenden Betriebe.

Zur Einschätzung der Waldentwicklung und des Rohholzaufkommens wurden in der Waldwachstumssimulationssoftware *WaldPlaner* der NW-FVA (Hansen & Nagel, 2014) aus den BWI-Daten Modellbestände generiert und bis zum Jahr 2042 fortgeschrieben. Die Parametereinstellungen zur Bestandesbehandlung orientierten sich an vorangegangenen Clusterstudien (Hansen et al., 2008; Wördehoff et al., 2011). In den Schutzgebieten wurde, je nach Schutzstatus, auf Nutzungen verzichtet bzw. es wurden abweichende Behandlungsparameter gewählt, um die spezifischen Nutzungsein-

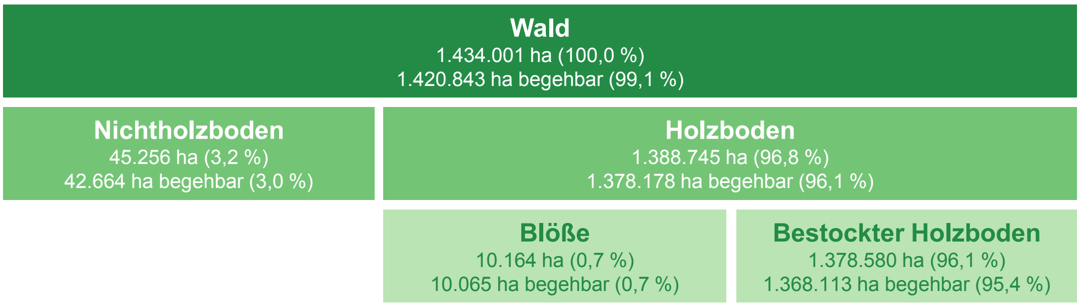

Abbildung 2.1: Waldkategorien in der Projektregion nach BWI-Definition (ML, 2014). Dauerhaft unbestockte Waldflächen, wie Waldwege, Wildwiesen oder im Wald gelegene Moore, werden als Nichtholzboden bezeichnet. Blößen sind vorübergehend unbestockte Waldflächen.

schränkungen der Flächen abzubilden. Gleichzeitig wurde unterstellt, dass die gewählten waldbaulichen Regeln und die Nutzungseinschränkungen über die gesamte Simulationsperiode unverändert gelten. Die simulierte Bestandesentwicklung wurde anhand der tatsächlichen Waldentwicklung seit der Vorgängerinventur (BWI 2) validiert.

2.3 Ergebnisse

2.3.1 Waldfläche

Mit einer Waldfläche von gut 1,4 Mio. ha liegt ca. 13 % des deutschen Waldes (TI, 2014) in der untersuchten Projektregion (Abbildung 2.1). Der Bewaldungsanteil in der Projektregion beträgt 31 %. Dies entspricht in etwa dem Bundesdurchschnitt von 32 % (TI, 2014). Der Waldanteil ist jedoch regional unterschiedlich. Er liegt zwischen 17 % im Westen Sachsen-Anhalts und 35 % in Südniedersachsen und Nordhessen.

Die Wälder der in weiten Teilen durch mesotrophe und eutrophe Lehmböden geprägten Mittelgebirgslandschaft (Gauer, 2012) zeichnen sich durch einen hohen Anteil von Laub- und Mischbeständen aus. Mit 36 % liegt der Laubwaldanteil deutlich über dem Nadelwaldanteil, welcher nur 14 % beträgt. Die Hälfte der Waldecken ist demnach mit Mischwäldern bestockt. Lediglich 18 % der Waldfläche in der Region hat nur eine Baumart in der Hauptschicht. Ebenso zeichnen sich die Wälder der Region durch eine starke vertikale Differenzierung aus. Zwei Drittel der Wälder haben mindestens zwei Bestandesschichten.

Im Rahmen der BWI wurden 86 Baumarten unterschieden. Um einen vertretbaren Schätzfehler und somit eine fundierte Aussage zu gewährleisten, wurden diese zu 8 Baumartengruppen (im Folgenden als Baumart bezeichnet) zusammengefasst. Wie aus Abbildung 2.2 hervorgeht, ist die Rotbuche am Inventurzeitpunkt die am weitesten verbreitete Baumart in der Projektregion. Mit Ausnahme des Nordostens ist die Projektregion durch eine ganzflächige, homogene Buchenwaldverteilung ohne systematische Muster und ohne regionale Schwerpunkte charakterisiert. Mehr als jeder zweite Waldtrakt weist eine Buchenbeimischung von über 33 % auf. Der Buchenanteil an der gesamten bestockten Holzbodenfläche beträgt 33 %, was einer Fläche von etwa 445.000 ha entspricht. Des Weiteren sind die Baumarten Fichte (*Picea spec.* inkl. *Abies spec.*, 22 %), Eiche (*Quercus robur* [L.], *Quercus petraea* [Matt.] und *Quercus rubra* [L.], 12 %) und Kiefer (*Pinus spec.*, 7 %) in größeren Anteilen in der Projektregion vertreten. Andere Laubbaumarten mit hoher Produktionszeit (ALh), zu denen u. a. Ahorn (*Acer spec.*) und Esche (*Fraxinus excelsior* [L.]) zählen,

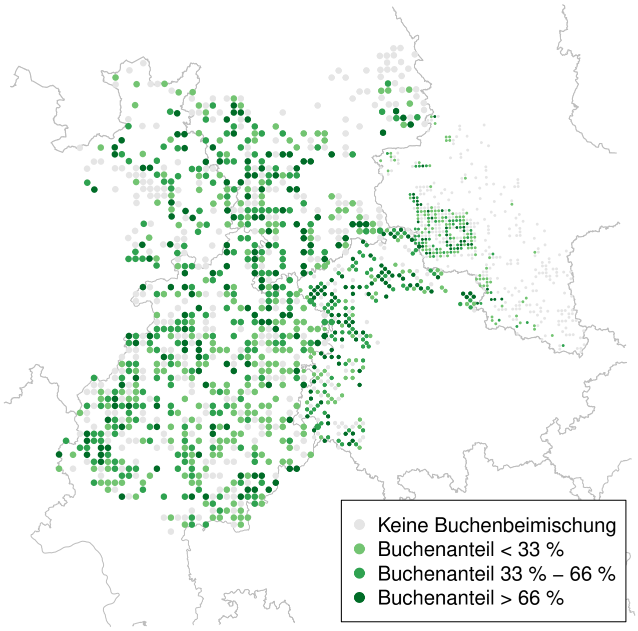

Abbildung 2.2: Buchenanteil an den BWI-Waldtrakten in der Projektregion. Die unterschiedlichen Punktgrößen ergeben sich aus den unterschiedlichen Traktabständen. Der Baumartenanteil bezieht sich auf den Hauptbestand, also die Bestandesschicht, auf der der wirtschaftliche Schwerpunkt liegt.

sowie andere Laubbaumarten mit niedriger Produktionszeit (ALn), zu denen u. a. Birke (*Betula spec.*) und Pappel (*Populus spec.*) gerechnet werden, sind jeweils mit etwa 10 % Flächenanteil vertreten. Lärche (*Larix spec.*) und Douglasie (*Pseudotsuga menziesii* [Franco]) spielen demgegenüber eine untergeordnete Rolle. Die Baumartenzusammensetzung findet sich in dieser Form in allen Eigentumsarten.

Das Mischungsverhältnis der Baumarten hat sich seit 2002 zugunsten der Laubbaumarten verändert. Im Vergleich zur BWI 2 ist die Laubwaldfläche bis 2012 um 52.000 ha angestiegen. Dem Anstieg der Laubwaldfläche steht ein deutlicher Rückgang der Nadelwaldfläche von etwa 40.000 ha gegenüber. Verantwortlich hierfür ist der Flächenverlust der Fichte in Höhe von etwa 35.000 ha und der Kiefer in Höhe von etwa 10.000 ha. Flächenzunahmen (ca. 5.000 ha) sind beim Nadelholz nur bei der Douglasie zu verzeichnen.

2.3.2 Alter des Waldes

Im Altersaufbau (Abbildung 2.3) spiegelt sich die Nutzungsgeschichte und natürliche Entwicklung der Wälder in der Projektregion wider. Insbesondere großflächige Erst- und Wiederaufforstungen nach dem zweiten Weltkrieg sowie nach dem Orkan 1972 prägen die Altersklassenstruktur im Nadelwald, da für die Wiederbepflanzung der Freiflächen zu der Zeit überwiegend Nadelbaumarten verwendet wurden (HMUKLV, 2014; ML, 2014). Aufgrund dessen ist mehr als die Hälfte des Nadelwaldes jünger als 60 Jahre. In den Altersklassen 20 bis 60 Jahre dominieren die Nadelbaumarten, während in der Altersklasse 1 bis 20 Jahre sowie dem Jungwuchs unter Schirm die Laubbaumarten deutlich überwiegen. Die Laubbaumanreicherung in den Jungbeständen spiegelt das Umdenken im waldbaulichen Handeln Anfang der 1990er-Jahre nach den Erfahrungen des *Waldsterbens* wider.

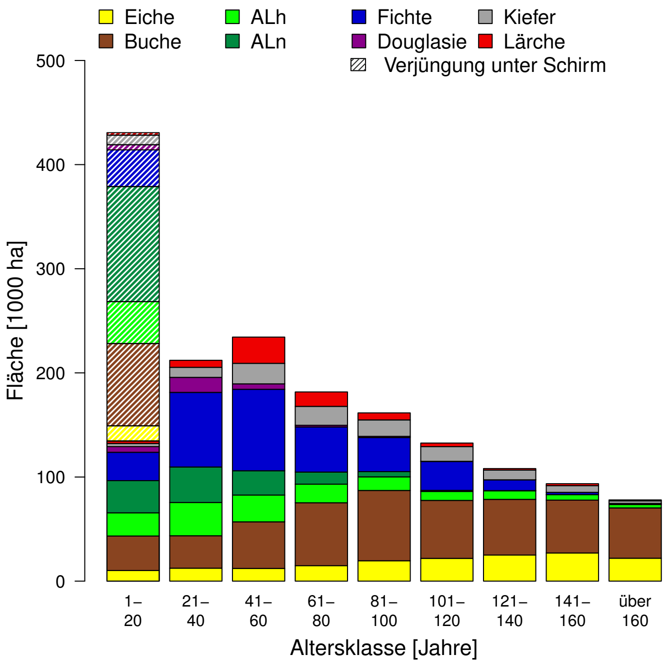

Abbildung 2.3: Bestockte Holzbodenfläche nach Altersklasse und Baumartengruppe in der Projektregion. Bei der Jungwuchsfläche unter Schirm wurde kein Baumalter erhoben. Sie wird per Definition der ersten Altersklasse zugeordnet.

Sie wurde relativ schnell flächenwirksam, weil die Orkane im ersten Jahrzehnt der 2000er-Jahre vor allem im Süden der Projektregion zu größeren Flächenverlusten im Nadelholz führten, die häufig mit Laubbaumarten wieder aufgeforstet wurden (HMUKLV, 2014). Unter Berücksichtigung der Voranbauten unter Schirm weisen die Laubbaumarten Buche und Eiche einen sehr ausgeglichenen Altersklassenaufbau auf. Diese Verjüngungsfläche unter Schirm muss für eine vollständige Darstellung der Ausgangssituation unbedingt mit berücksichtigt werden. Da in diesen Fällen zwei Bestandesschichten auf gleicher Fläche stocken, werden die Jungwuchsbestände unter Schirm als überschießende Flächen bezeichnet, welche nicht zum Hauptbestand zählen und somit nicht in die Berechnung der bestockten Waldfläche eingehen. Andernfalls würde die tatsächliche Waldfläche um die Fläche des Jungwuchses überschätzt werden.

2.3.3 Waldeigentum

Mit einem Flächenanteil von jeweils 35 % an der Waldfläche dominieren Privat- (inkl. privatrechtlicher Organisationen) und Landeswald vor dem Körperschaftswald (24 %), also Wald im Eigentum von Städten oder Gemeinden sowie Körperschaften, Anstalten oder Stiftungen öffentlichen Rechts. Bundes- und Treuhandwald spielen eine untergeordnete Rolle. Wald im Landesbesitz, der von Anstalten oder Körperschaften öffentlichen Rechts bewirtschaftet wird, ist als Landeswald definiert. Die Betriebsgröße ist ein wichtiges Strukturmerkmal zur näheren Beschreibung des Privatwaldes, da sie Hinweise auf Organisationsgrad und Leistungsfähigkeit eines Forstbetriebes gibt. Etwa ein Drittel der Privatwaldfläche, also ca. 11 % der Gesamtwaldfläche, ist kleinen Privatforstbetrieben mit einer Betriebsgröße unter 20 ha Betriebsfläche zuzuordnen. Demgegenüber entfallen 60 % des Privatwaldes auf größere Forstbetriebe über 100 ha. Im Vergleich zum Bundesschnitt (TI, 2014) sind die Privatforstbetriebe der Projektregion damit tendenziell größer. In der räumlichen Vertei-

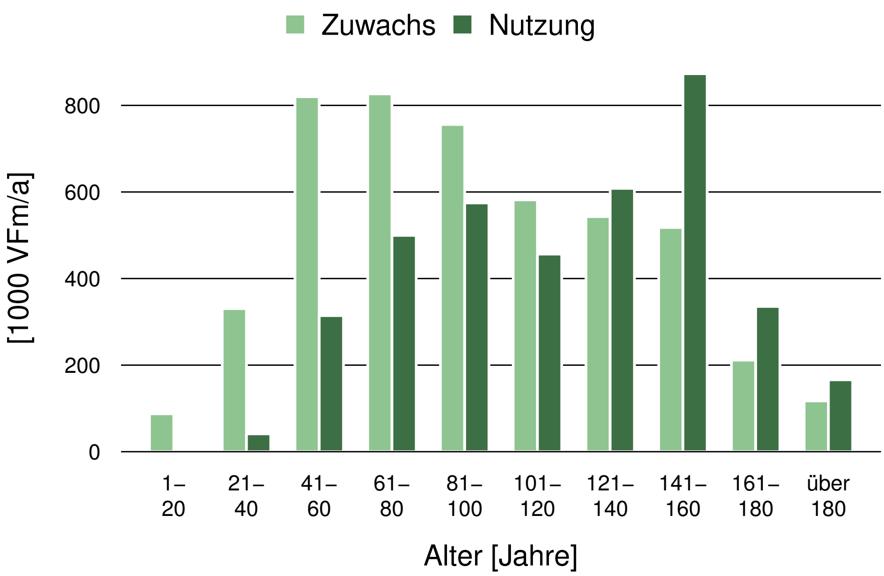

Abbildung 2.4: Durchschnittlicher jährlicher Vorratszuwachs und durchschnittliche jährliche Holznutzung der Buche nach Altersklasse in der gesamten Projektregion für den Zeitraum 2002 bis 2012. Die Holznutzung beinhaltet sowohl gewerbliche als auch private Nutzungen.

lung der 3 Haupteigentumsarten sowie der Größenklassen im Privatwald bestehen keine regionalen Unterschiede. Jede Eigentumsart und jede Größenklasse im Privatwald ist näherungsweise homogen in der gesamten Projektregion vertreten.

2.3.4 Nachhaltiges, kontinuierliches Holzpotenzial

Nach Speidel (1972) ist die nachhaltige Forstwirtschaft als "Fähigkeit eines Forstbetriebes, kontinuierlich und optimal Holznutzungen, Infrastrukturleistungen und sonstige Güter zum Nutzen der gegenwärtigen und zukünftigen Generationen hervorzubringen"definiert. Während sich die Eingriffe in den jüngeren Altersklassen auf die Pflege der Bestände beschränken, die Zuwächse nur teilweise abgeschöpft und die Holzvorräte dementsprechend aufgebaut werden, führen die Hauptnutzungen in den älteren Altersklassen zu einem mehr oder weniger schnellen Vorratsabbau, um die höherwertigen Stammholzsortimente zu nutzen und die Verjüngung einzuleiten bzw. um über der neuen Waldgeneration den Altholzschirm schrittweise zu räumen. Dieses Nutzungsverhalten spiegelt sich in den zwischen BWI 2 und BWI 3 beobachteten Relationen von Holznutzung zu Holzzuwachs bei der Buche wider (Abbildung 2.4). Während der Holzzuwachs die Nutzung bis zu einem Bestandesalter von 120 Jahren übersteigt, überwiegt die Nutzung ab 140 Jahren deutlich.

Durch das multifunktionale Nachhaltigkeitsverständnis der deutschen Forstbetriebe, wie es auch in den Waldgesetzen verankert ist, werden auf derselben Fläche grundsätzlich Nutz-, Schutz- und Erholungsfunktionen gleichzeitig, aber mit lokal unterschiedlicher Gewichtung verfolgt (Möller, 2007). Dieser integrative Ansatz erfordert, die Wechselwirkungen zwischen Nutzungs- und Naturschutzaspekten flächendeckend abzuwägen und in Einklang zu bringen. In der Projektregion unterliegen annähernd 75 % der Waldfläche mehr oder weniger restriktiven Schutzgebietsauflagen (Abbildung 2.5). Davon sind ca. 10.000 ha der strengsten Schutzkategorie Nationalpark zuzuordnen, wobei die BWI nicht zwischen Kernzonen ohne Nutzung und Entwicklungszonen mit Nutzung unterscheidet. Die Nutzung ist demnach nicht auf der gesamten Fläche ausgeschlossen, jedoch zu-

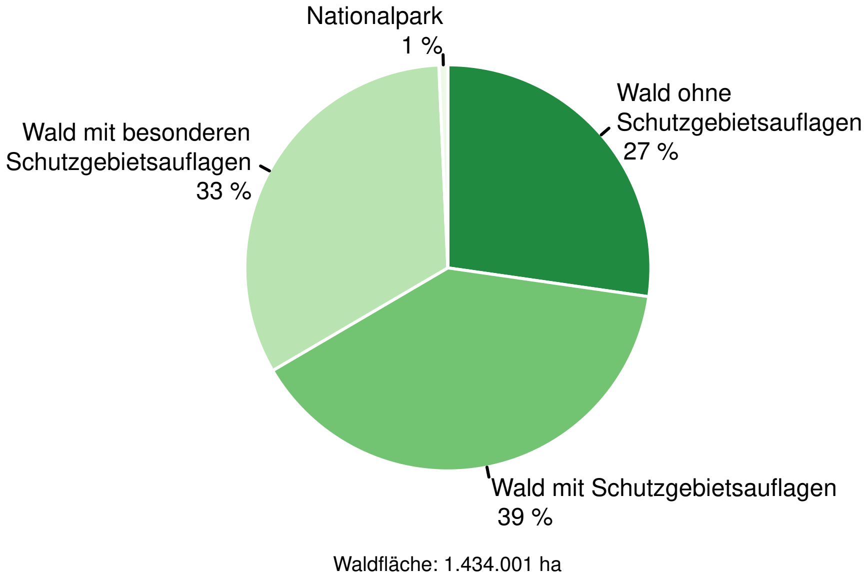

Abbildung 2.5: Schutzgebietsauflagen der Waldflächen in der Projektregion.

mindest sehr stark eingeschränkt. Ein Drittel der Waldfläche unterliegt hohen Schutzgebietsauflagen. In diese Kategorie fallen Biosphärenreservate, Naturschutzgebiete und Natura 2000-Flächen. Auf diesen Flächen kann je nach Schutzgebietsart mit einer verminderten Holznutzung gerechnet werden. Ein Nutzungsausschluss ist jedoch in der Regel nicht zu erwarten. Hinzu kommen 560.000 ha auf denen Erholung, Erhaltung des Landschaftsbildes oder Wasserschutz im Vordergrund stehen. Auf diesen Flächen ist nicht von Nutzungseinschränkungen aufgrund des Schutzstatus auszugehen, es muss jedoch teilweise mit erschwerten Erntebedingungen gerechnet werden.

Unter Berücksichtigung der Schutzgebietskulisse sowie der Altersausstattung des Waldes in der Projektregion betrug der jährliche Holzzuwachs der Buche nach BWI-Berechnungen in der Periode 2002 bis 2012 durchschnittlich 3,9 Mio. Vfm Jahr^{-1}. Demgegenüber stand die durchschnittliche jährliche Nutzung, welche ebenfalls über die BWI-Daten berechnet werden konnte, von 3,8 Mio. Vfm Jahr^{-1}. Trotz des rechnerischen Abzugs des nicht-nutzbaren Holzzuwachses vom Gesamtzuwachs lag der Zuwachs in der Bilanz der 10-jährigen Periode von 2002 bis 2012 noch leicht über der Nutzung. Der Gesamtzuwachs inkl. aller Altersklassen und Schutzgebietskategorien betrug 4,8 Mio. Vfm Jahr^{-1}. Das durchschnittlich genutzte Holzvolumen von 3,8 Mio. Vfm Jahr^{-1} entspricht, nach Abzug von Rinde und Ernterückständen, einem Rohholzvolumen von 3,5 Mio. Efm Jahr^{-1}. Dieses lässt sich mit BWI Daten nicht nach Sortimenten für bestimmte Holzverwendungen aufschlüsseln. Aus diesem Grunde fand im Rahmen des Projektes eine Befragung und Einschätzung des Einschnitts der wichtigsten buchenholzverarbeitenden Betriebe statt, die ihr Rohholz aus der Projektregion beziehen. Darüber hinaus wurden die Exportmengen eingeschätzt. Die Analyse zeigte, dass durch die buchenholzverarbeitenden Betriebe sowie den nationalen und internationalen Holzexport jährlich ca. 1 Mio. Efm Jahr^{-1} Stammholz (inkl. Palettenholz) und 1 Mio. Efm Jahr^{-1} Industrieholz aus der Projektregion aufgenommen wurden. Dies entsprach etwa 60 % der tatsächlichen jährlich eingeschlagenen Rohholzmenge. Es ist davon auszugehen, dass die restlichen 1,5 Mio. Efm Jahr^{-1} nahezu komplett energetisch verwendet wurden. Diese Einschätzung deckt sich in etwa mit den Ergebnissen einer Umfrage von knapp 10.000 Haushalten in ganz Deutschland durch die Universität Hamburg (Mantau, 2012), wonach deutschlandweit im Jahr 2010 knapp ein Drittel des Waldlaubholzaufkommens im Durchschnitt direkt energetisch genutzt wurde.

2.3.5 Entwicklung des Rohholzvorrates und des Rohholzpotenzials

Im Folgenden wird nicht nur das Rohholzpotenzial, sondern auch die prognostizierte Waldentwicklung in Vorratsfestemetern angegeben. Dies hat gegenüber einer reinen flächigen Betrachtung den Vorteil, dass Bäume aller Bestandesschichten berücksichtigt sind und sich keine rechnerischen Schwierigkeiten durch überschießende Flächen ergeben. Ferner bewirkt jeder Vorratsaufbau und -abbau auch eine Veränderung der Bestandesdichte und somit des Gesamtvorrates. Bei einer flächigen Betrachtung wären Veränderungen der Bestandesdichte nicht ersichtlich. Der Gesamtholzvorrat der Projektregion ist demnach eine abstrakte Kennzahl, aus welcher sich wesentliche Rückschlüsse auf Produktivität, nachhaltige Nutzungsmöglichkeiten und die wirtschaftliche Leistungsfähigkeit der Forstbetriebe in der Projektregion ableiten lassen. Die Vorratsberechnungen 2002 und 2012 basieren auf BWI Daten, die Vorratsprognosen ab 2022 auf Waldentwicklungssimulationen.

Zwischen 2002 bis 2012 nahm der Buchenvorrat in allen Ländern der Projektregion um insgesamt ca. 13 Mio. Vfm zu. Der Vorratsaufbau war im Landeswald stärker ausgeprägt als im Privat- und Körperschaftswald. Im Vergleich der Baumarten Fichte und Kiefer ergab sich ein inhomogenes Bild. In Niedersachsen und Thüringen gab es, bedingt durch den jüngeren Altersaufbau, einen Vorratsaufbau, in Hessen und Nordrhein-Westfalen einen etwa gleichstarken Vorratsabbau. Obwohl es nennenswerte Flächenverluste bei diesen Baumarten gab (siehe Kapitel Waldfläche), blieb der Vorrat der Fichte und Kiefer zwischen 2002 und 2012 aufgrund des hohen Flächenanteils der zuwachsstarken Altersklassen unverändert.

Die Simulationsergebnisse (Abbildung 2.7) lassen einen kontinuierlichen Anstieg des Gesamtvorrates bei der Buche erwarten. Er ist im Jahr 2042 unter der Annahme unveränderter waldbaulicher Vorgaben voraussichtlich etwa 25 % höher als 2002. Während die Vorräte der Eiche und der ALn stagnieren, steigt der Vorrat bei den ALh stetig an. Der Gesamtvorrat von Fichte und Kiefer nimmt bis einschließlich 2022 leicht ab. Ab 2022 wächst ein Großteil dieser Nadelholzbestände in die Hiebsreife und der Vorrat nimmt ab diesem Zeitpunkt bis zum Ende der Simulation stetig ab. Bis zum Jahr 2042 wird der Holzvorrat der Fichten- und Kiefernbestände voraussichtlich um jeweils ein Drittel zurückgehen. Trotz einer Verdreifachung ihres Vorrates spielt die von einem niedrigen Ausgangsvorrat kommende Douglasie auch 2042 weiterhin nur eine untergeordnete Rolle in der Projektregion. Dieser Vorratszuwachs ist fast ausschließlich durch den hohen Zuwachs der bereits etablierten, zum Start der Simulation überwiegend jungen Bestände begründet. Die Lärche spielt ebenfalls nur eine untergeordnete Rolle in der Region. Ihr Vorrat stagniert auf einem relativ niedrigen Niveau. Der Gesamtholzvorrat wird in den kommenden Jahren voraussichtlich zunächst stagnieren und ab 2032 leicht sinken.

Der laufende jährliche Holzzuwachs je ha der Fichte liegt im bundesdeutschen Durchschnitt über alle Altersklassen etwa 50 % über dem laufenden jährlichen Zuwachs der Buche (TI, 2014). Die Waldumwandlung von Fichten- in Buchen- und in Mischbestände wird demnach nicht nur zu einer Verringerung der durchschnittlichen Bevorratung in der Projektregion führen, sondern langfristig auch das Zuwachsniveau und somit das Rohholzpotenzial insgesamt senken. Das voraussichtliche Nutzungspotenzial der Buche stagniert zunächst bis 2031 auf einem Niveau von ca. 4 Mio. Vfm und steigt danach auf 4,8 Mio. Vfm an. Der Vorratsabbau in den vorratsreichen Nadelholzaltbeständen wird im Simulationszeitraum zu einer Erhöhung des Fichten Rohholzaufkommens führen. Hierbei wird vor allem hiebsreifes Stammholz aus den Endnutzungen anfallen.

Das gesamte Nutzungspotenzial in der Projektregion steigt deshalb in der Simulationsperiode stetig um etwa 3 % je Jahrzehnt an. Hierbei werden neben unveränderten waldbaulichen Konzepten auch das Ausbleiben von Großschadereignissen oder Ausweitungen der Schutzgebietskulisse unterstellt.

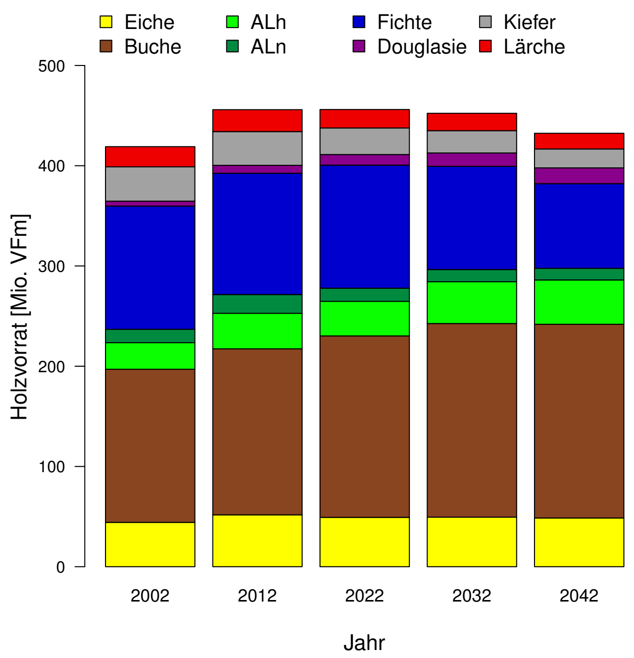

Abbildung 2.6: Entwicklung des Gesamtvorrates nach Baumartengruppe in der Projektregion. Die Gesamtvorräte der Jahre 2002 und 2012 wurden aus den BWI Daten berechnet. Die Vorräte ab 2022 wurden mit der Waldwachstumssimulationssoftware *WaldPlaner* prognostiziert.

2.4 Konsequenzen für die Nutzung von Buchenholz

In der vorgestellten Projektregion hat die Laubholzwirtschaft eine große Bedeutung. Das Buchenrohholzpotenzial ist nicht nur hoch, sondern aufgrund des hohen Buchenwaldanteils (Abbildung 2.2) und dessen relativ ausgeglichenen Altersklassenaufbaus (Abbildung 2.3) gut sortiert. Ohne lange Transportwege sind alle holzwirtschaftlich relevanten Rohholzdimensionen verfügbar.

Da die Wertschöpfung beim Stammholz am höchsten ist, zielt die Buchenwirtschaft auf eine möglichst hohe Stammholzausbeute ab (Nagel & Spellmann, 2008). Dieses Stammholzpotenzial steht in den vorratsreichen Altholzbeständen der Projektregion zur Verfügung und ein nachhaltiger Nachschub ist durch die ausreichenden Flächen der mittleren Altersklassen zwischen 81 und 100 Jahren auch in Zukunft sichergestellt. Des Weiteren ist das Potenzial der schwächeren Holzsortimente, insbesondere bei der Buche, nicht zu unterschätzen. Industrieholz als Koppelprodukt der Stammholzernte und als Vornutzungsmaterial aus den jüngeren Beständen unter 80 Jahren gewährleistet die Rohstoffversorgung der Zellstoff- und Holzwerkstoffindustrie sowie der Heizkraftwerke und des Hausbrandes mit schwächer dimensionierten Sortimenten. Die homogene räumliche Verteilung der Eigentumsarten mit relativ großen Privatwaldbetrieben lässt auf eine effektive Laubrohholzbereitstellung mit geringen regionalen Unterschieden schließen. Nicht zuletzt aus diesem Grund sind auch viele der deutschen Laubholzsägewerke in dieser laubbaumreichen Region konzentriert (Ochs et al., 2007).

Das um alters- und schutzstatusbedingte Nutzungseinschränkungen bereinigte, nachhaltig nutzbare Buchenrohholzpotenzial der Projektregion wurde zwischen 2002 und 2012 fast komplett genutzt, wobei knapp drei Viertel der anfallenden Menge von der Säge- und Holzwerkstoffindustrie aufgenommen wurde. Die Unternehmen der Holzindustrie nutzen den zur Verfügung stehenden

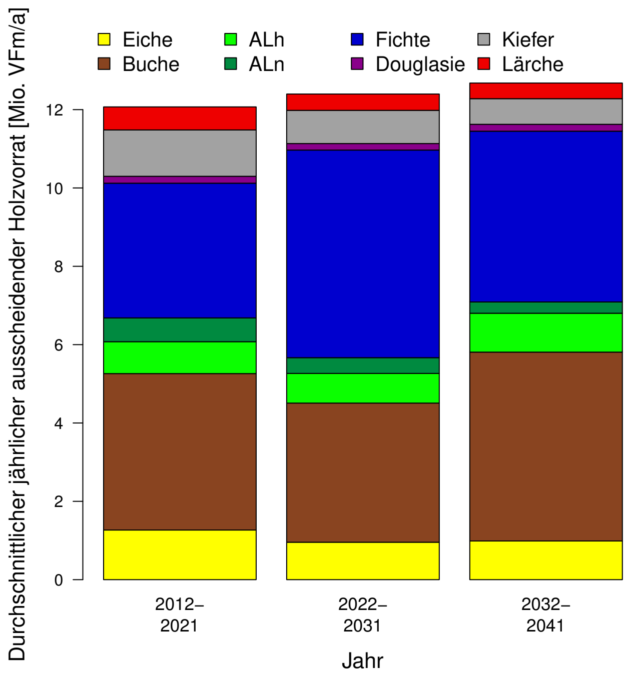

Abbildung 2.7: Simulierte Entwicklung des Rohholzeinschlags nach Baumartengruppe in der Projektregion. Die Vorräte wurden mit der Waldwachstumssimulationssoftware *WaldPlaner* prognostiziert.

Holzzuwachs im Laubholz demnach zurzeit sehr effektiv. Größere zusätzliche Nutzungspotenziale lassen sich bei der Buche kurzfristig allenfalls durch eine Intensivierung der Holznutzung in den Beständen über 140 Jahren erschließen. In diesen Altholzbeständen ist oft kein weiterer Anstieg der Wertschöpfung zu erwarten. Jedoch muss gerade in diesen Altholzbeständen berücksichtigt werden, dass die Verjüngung der nächsten Waldgeneration sichergestellt ist und dass naturschutzfachliche Aspekte beachtet werden. Weitere Nutzungspotenziale für die Holzwerkstoff- und ggf. die Chemieindustrie liegen im Energieholzbereich. Wenn die Wertschöpfungskette einen konkurrenzfähigen Holzpreis oberhalb des lokal sehr unterschiedlichen Energieholzpreises erlaubt, könnten Teile des bisher direkt energetisch genutzten Holzvolumens einer höherwertigeren Verwendung zugeführt werden und je nach Nutzungsform durch Kaskadennutzung teilweise am Ende der Produktlebensdauer energetisch verwendet werden (Rüther et al., 2007). Die angespannte Konkurrenzsituation beim Buchenindustrieholz, welche sich durch die hohe Nachfrage nach Holz als Energieträger (Mantau, 2012) und der Etablierung neuer Geschäftsfelder, wie der Bioökonomie (McCormick & Kautto, 2013), begründet, spiegelt sich in der Verdopplung des jährlich durchschnittlichen Buchenindustrieholzpreises in Deutschland seit 2005 wider (DESTATIS, 2016). Aufgrund dieses stetigen Anstiegs setzen die Industrieholzverbraucher in der Projektregion immer stärker auf internationalen Holzimport und Altholzankauf. Der milde Winter, die Verfügbarkeit von Landschaftspflegeholz und die niedrigen Öl- und Gaspreise führen aktuell zu einer Verringerung der Nachfrage nach Industrieholz als Energieträger. Zurzeit ist neben einer Entspannung auch ein Überhang an heimischem Buchenindustrieholz zu beobachten. Dieses spiegelt sich jedoch noch nicht im Jahresdurchschnitt der Holzpreisstatistiken wider.

Viele der erntereifen Kiefern- und Fichtenreinbestände werden im Simulationszeitraum voraussichtlich zu Laubbaum- oder Mischbeständen überführt. Dieser Trend lässt sich seit 2002 aus den BWI Daten ablesen (Fischer & Husmann, 2016) und wird voraussichtlich in der Simulationsperiode noch andauern (ML, 2004; BMEL, 2011). Die prognostizierte Verschiebung des Vorrates hin zu mehr Laubbaumarten (Abbildung 2.7) spiegelt also die Konsequenzen aus der aktuellen Waldpolitik wider. Da der Volumenzuwachs in Laubbaumbeständen meist deutlich geringer als in Nadelbaumbeständen ist, tragen die neubegründeten Laub- und Mischwälder im Durchschnitt weniger zum Vorratsaufbau bei als die reinen Nadelwälder, aus denen sie hervorgegangen sind. In der Projektregion verläuft der Vorratsaufbau der Buche deshalb langsamer als der Vorratsabbau der Fichte und Kiefer, was zur Stagnation und letztlich zur leichten Abnahme des gesamten Holzvorrates in der Projektregion führen wird.

Da sich die Struktur des Holzmarkts in der Vergangenheit stetig verändert hat (Ochs et al., 2007) und durch die Etablierung neuer Geschäftsfelder auch aktuell im Wandel ist (McCormick & Kautto, 2013), gestalten sich Prognosen über die Zukunft des Holzmarktes sehr schwierig. Aus diesem Grunde wurden keine Annahmen zur Entwicklung der Holznachfragemenge getroffen. Aus den Auswertungen wurde lediglich klar, dass das Holzpotenzial zwischen 2002 und 2012 weitestgehend ausgeschöpft wurde. Durch die mittelfristige Erhöhung des Nadelholzangebots wird sich das Gesamtrohholzpotenzial zunächst erhöhen. Bedingt durch den fortschreitenden Umbau der Nadelholzbestände in Misch- oder Laubholzbeständen folgt diesem voraussichtlichen mittelfristigen Anstieg jedoch ein stetiger Rückgang des Rohholzangebotes. In der Projektregion Bei zukünftigen Investitionen oder Fördermaßnahmen muss deshalb unbedingt beachtet werden, dass die sich abzeichnende Erhöhung des gesamten Rohholzangebots nur eine zeitlich begrenzte Phase ist. Die Implementation zusätzlicher Schutzgebiete würde das Rohholzpotenzial zusätzlich reduzieren.

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Chapter 3

Biomass functions and nutrient contents of European beech, oak, sycamore maple and ash and their meaning for the biomass supply chain

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- Jürgen Nagel supported writing of the manuscript and the review process.

Abstract

Woody biomass from forests has great potential to provide a continuous and largely carbon-neutral raw material supply for the bio-based industry. As the demand for forestry products is already very high and steadily increasing, the question arises how to match the limited available wood resources to the growing demand for raw materials. Thus, there is an initial need to properly estimate the available biomass from forests. The success of a bio-based industry depends on an accurate forecast of the raw material flow coming from the forests for the entire biomass supply chain up to the industrial processing stage. Using easily measured input data, e. g. the tree diameter at breast height, biomass functions allow for a reliable prediction of tree species- and tree fraction-specific single-tree biomasses. In combination with nutrient content data, the site specific ecologically sustainable level of forestry use can be assessed and the site-specific wood utilization potential can be fully exploited.

Biomass functions for the main tree species can be found in the literature. For other tree species, like sycamore or ash, however, there are only very specific studies available. As the wood potential of especially those species is recently often unused, goal of this study is to develop biomass functions and nutrient contents for European beech, oak, ash and sycamore for the fractions stem wood, bark, branches, and twigs.

For this purpose 139 trees were destructively sampled. Their single tree biomasses and nutrient contents were examined. This data was then used in a regression analysis to build generalized tree species- and tree fraction-specific biomass functions and nutrient contents for northern and central Germany. We showed that the sycamore and ash biomass functions differed significantly from those of European beech and oak. Using oak biomass functions for the biomass estimation of sycamore and ash, as it is practiced today, leads to a massive overestimation of the standing biomass in a test site up to 11 % (21 tons / ha respectively).

The share of species-rich broadleaf forest stands, and thereby the importance of tree specific biomass functions, is increasing. The introduced models can help to exploit the huge biomass potential of those deciduous stands.

Keywords

Biomass function - Nutrient content - Long-living tree species - Biomass supply chain - Site sustainability

Highlights

– Effectivity of biomass supply chains depend on reliable biomass estimation.

– The wood potential of long-living tree species is recently often unused.

– Biomass models for sycamore maple and ash can help gathering this potential.

3.1 Introduction

Biomass from forests has real potential to provide a continuous and largely carbon-neutral supply of material to the bio-based industry sector and can therefore make a significant contribution to a clean bio-based industry. Especially small dimensioned wood has huge potential for use in bio-refineries. Ekman et al. (2013) showed in Sweden that previously unused scrap wood can be used for the extraction of high quality chemical substances, such as bio-oils or antioxidants for use in the food or cosmetics industries. Supply of biomass from forestry can drive the economic growth of the entire bio-based chemical industry and make it competitive in the long-term, especially if wood fractions that have up to now been used as fuel wood are included. Innovative industries, such as the nanofiber or biochemistry industries, are increasing the demands on the forestry product-pool. The forest-based bio-economy is already an integral part of the global forestry sector (Hurmekoski & Hetemäki, 2013). The European bio-based industry is currently a growing sector, with Germany playing a leading role (Hennig et al., 2016).

The global forestry industry is currently undergoing a process of change. The use of wood as raw materials in Germany has increased considerably in the last decades Mantau (2012). Changes in government energy policy and the development of new technology led to development of new markets, in particular for small dimensioned wood (Geldermann et al., 2016; McCormick & Kautto, 2013). The demand for forestry products is steadily rising, increasing the competition for raw timber. The question then is how to match the available wood resource to the demand for raw materials.

Just as it is for classical forestry (Möhring, 1997), knowledge of the available potential biomass is the main prerequisite for a functioning bio-based industry (Hennig et al., 2016). Using wood means that the nutrients bound in the wood are removed from the forest ecosystem. The biomass potential of a forest can only be utilized to an extent that, in the long-term, won´t deplete the supply of plant available nutrients in the forest ecosystem. In order to be able to exploit the woody biomass potential for the bio-based industry, the limit of the utilisation extend from the forests stands must be known (Block et al., 2013; Pretzsch et al., 2014). Therefore, reliable estimates of the quantity of biomass to be harvested, as well as reliable estimates of the amount of nutrients contained in these biomasses are required.

Using easily measured input data, such as diameter at breast height (dbh) or tree height, biomass functions enable the prediction of single-tree biomasses. Tree species and tree-fraction specific estimations of the forest biomass supply can be made. Using these biomass functions coupled with nutrient content data, the nutrient export can be estimated. In this way an ecologically sustainable level of forestry use can be calculated and the site specific wood utilization potential can be fully exploited.

The success of the bio-based industry depends to a great extent on the ability to accurately forecast the flow of raw materials in the integrated biomass supply chain (Geldermann et al., 2016; How et al., 2016). Using biomass functions the relevant information for strategic operational decision-making can be generated for the entire biomass supply chain - from the forest stand to the industrial processing stage. Detailed biomass calculations can improve planning certainty along the entire value chain because the masses to be transported and those due at the factory gate can be forecasted very accurately. Biomass functions can therefore make an important contribution to increasing the planning capability, and thereby to cost reductions, in operative planning for forestry enterprises, wood logistics and wood industry firms.

Wood industry cluster studies on the availability of raw materials and on the market situation of the wood industry are the bases for the strategic orientation of the bio-economy industries (McCormick & Kautto, 2013). By using supply analyses and material flow simulations together with biomass functions decision support models can be parameterised which enable, for example, the computing of a continuous biomass supply chain (e.g. Rüther et al. (2007); Wördehoff et al. (2011); Mantau (2012)).

Responsible biomass usage from forests has, next to its economic relevance, also very important social impacts. In 2006, under the terms of the Kyoto protocol, reporting of the carbon sequestration performance of forests became mandatory in Germany. The use of biomass functions is an integral part of this reporting process (Vallet et al., 2006; Tabacchi et al., 2011; Wördehoff et al., 2011).

In the literature there are numerous biomass functions (e.g. Grote et al. (2003); Cienciala et al. (2005); Pretzsch et al. (2014)) and nutrient content figures (e.g. (Augusto et al., 2000; Jacobsen et al., 2003; Weis & Göttlein, 2012; Pretzsch et al., 2014)) available for the tree species European

Table 3.1: Descriptive statistics of the sampled trees.

		oak	European beech	ash	sycamore
	number of trees	40	37	37	25
dbh [cm]	minimum	8.00	8.00	9.10	12.00
	mean	35.40	32.50	31.90	28.20
	std. dev.	23.70	17.14	17.30	10.40
	maximum	95.40	66.40	75.60	56.10
height [m]	minimum	9.60	15.30	14.40	15.20
	mean	22.10	24.90	25.60	22.60
	std. dev.	6.90	6.65	6.70	4.25
	maximum	32.00	35.25	38.50	31.80
age [a]	minimum	25	21	34	33
	mean	86	84	74	51
	std. dev.	54	44	37	23
	maximum	190	180	153	118

beech (*Fagus sylvatica* [L.]), common oak (*Quercus robur* [L.]) and sessile oak (*Quercus petraea* [Matt.]). For sycamore maple (*Acer pseudoplatanus* [L.]) and ash (*Fraxinus excelsior* [L.]) however, there are only few functions available. All literature functions found either do not cover the entire relevant diameter spectrum (e.g. Albert et al. (2014); Alberti et al. (2005)) or do not allow fraction specific biomass estimation (Bunce, 1968).

The wood increment of long-term deciduous trees, which is the species group sycamore and ash belong to, was only used by 38 % between 2002 and 2012 (TI, 2014). This is certainly partially reasoned by the fact that reliable planning methods for long-term deciduous species are not available. The question then arises if the predictions of the woody biomass in these stands could be improved by using specific biomass functions and nutrient contents for sycamore and ash. Specific biomass functions for these species could help making the recently unused potential available for the bio-based industry.

The goal of this study is to develop biomass functions for European beech, oak, sycamore and ash by means of regression analysis, using data gathered in northern and central Germany. Functions are developed for the tree fractions stem wood (diameter > 7cm without bark), bark of stem wood, branches (1 - 7cm with bark), and twigs (< 1cm with bark). The differences in these biomass functions are examined at single-tree and stand level by means of a sensitivity analysis in an exemplary test stand. The nutrient content in the different tree fractions of the tree species studied are determined and used as the basis for quantifying the nutrient removal by harvesting. The amount of nutrients that are removed from the forest ecosystem is then determined by multiplying the nutrient content with the biomass.

3.2 Materials and Methods

With the goal of quantifying biomass and nutrient content 139 vital trees were studied (Table 3.1). The sample plots for beech and oak represented as many different growing areas and site conditions as possible. The high nutrient requirements of sycamore and ash meant that the sample plots for these species were exclusively on nutrient-rich, calcareous substrates. Per plot 2 - 4 trees were chosen (Figure 3.1). Both within each sample site, and across the plots as a whole, the aim was to collect trees from a wide and evenly distributed diameter range.

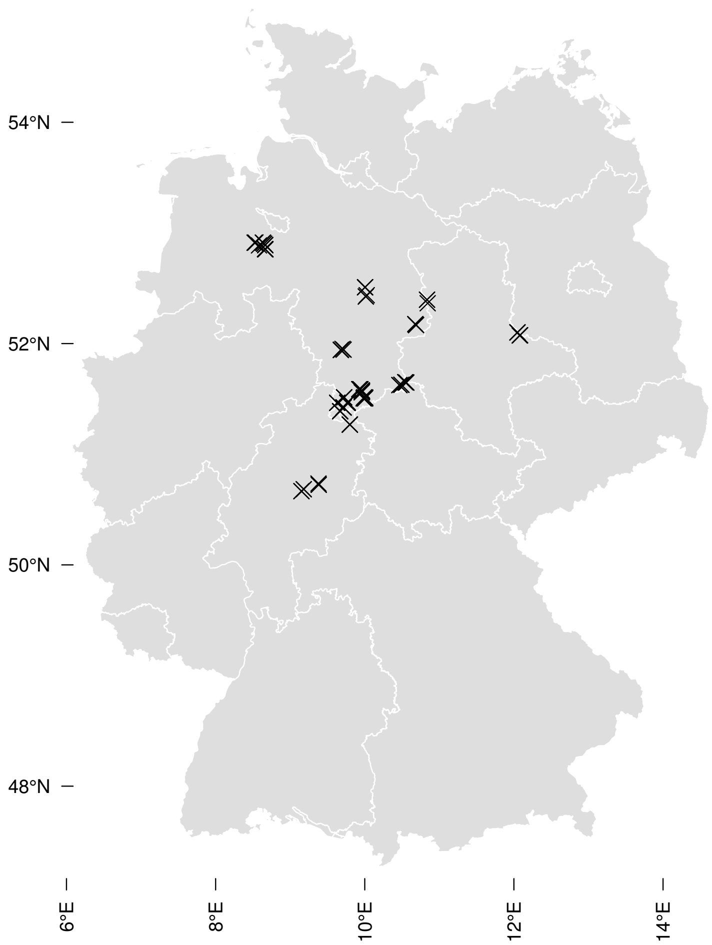

Figure 3.1: Locations of the 54 sampled plots. Source of the background map: FACG (2014).

3.2.1 Data sampling and sample processing

Dbh, height at crown base and tree height were measured for each tree. The fraction volumes of the trees were determined using randomized branch sampling (RBS). RBS is an efficient and bias free sampling method for estimating tree fractions (Saborowski & Gaffrey, 1999; Gregoire & Valentine, 2008). Since this method was firstly described Jessen (1955) it has been used in other studies, including those from Valentine et al. (1984), Gaffrey & Saborowski (1999) and Affleck & Gregoire (2015). This multi-stage sampling method assumes proportionality between the target quantity and an easily measurable proxy. Because an allometric relationship exists between branch volume and branch base diameter (West, 1999), the RBS method makes it possible to estimate the wood volume by measuring only a subset of branch lengths and branch diameters in the tree crowns. The stem form was assessed by section-wise diameter measurements at certain tree heights up to the crown base. In order to determine the specific bulk density and nutrient contents, up to 12 samples, covering all diameters of the tree, were collected per tree using the Importance Sampling (Gregoire & Valentine, 2008).

Half of the samples were measured and weighted in fresh state and, after several days drying at 103 °C, in absolute dry condition in order to determine the bulk density [kg biomass (dry) / m^3 wood volume (fresh)] (Rademacher et al., 2011). For all stem wood samples (diameter > 7cm) the bark was separated from the wood before drying. From this samples tree species and tree fraction specific bulk density coefficients were calculated. The fraction volumes, which were previously estimated using the RBS method, could then be converted into biomasses using these bulk density coefficients. The other half of the samples underwent a chemical analysis in order to determine their nutrient concentrations. In our sample preparation and analysis we followed the widely used method by König & Fortmann (2012b,a). In order to ensure comparability between all studied tree species, only European beech and oak samples from sample plots on nutrient-rich substrates were considered for the chemical analysis.

3.2.2 Biomass functions

In order to parameterize tree species and tree fraction dependent biomass functions the single-tree biomass information was analyzed by regression analysis. The biomass functions were estimated using nonlinear Generalized Least Squares Estimation. The exponential function used in Hochbichler et al. (2006) (Equation 3.1) was chosen as the model type (Rumpf et al., 2011). The validity of each model was tested via visual analysis of the weighted model residuals including a comparison with theoretical residuals (quantile-quantile-analysis). Furthermore the bias of each model was calculated as the mean of the model residuals.

$$\hat{Y}_i = \exp\left(\alpha + \beta\, ln(dbh_i) + \gamma\, ln(h_i)\right) \varepsilon_i \tag{3.1}$$

One general assumption in regression analysis is the independence of the model errors ε_i. Because this assumption is probably not met for the tree fractions within a tree species, a model distortion due to correlation between the covariates (collinearity) is possible. Not taking this collinearity into account can influence the results of a regression and thereby limit the model validity (Graham, 2003). In order to estimate the magnitude of the error resulting from collinearity, in addition to the single model variances $var(\hat{y}_i)$, combined model variances per tree species $\hat{\hat{y}}$ were calculated (Parresol, 2001). This combined model variance per tree species consists of the single model variances $var(\hat{y}_i)$ and the model co-variances $cov(\hat{y}_i, \hat{y}_j)$ between the fraction functions for a respective tree species (Equation 3.2). The correlation between two fractions was estimated using a linear correlation coefficient of the measured biomasses.

$$\begin{gathered} var\left(\hat{\hat{\mathrm{y}}}\right) = \sum_{i=1}^{c} var\left(\hat{\mathrm{y}}_\mathrm{i}\right) + 2\sum_{i<j}\sum cov\left(\hat{\mathrm{y}}_\mathrm{i}, \hat{\mathrm{y}}_\mathrm{j}\right) \\ \text{Where } c = \text{Number of biomass functions,} \\ cov\left(\hat{\mathrm{y}}_\mathrm{i}, \hat{\mathrm{y}}_\mathrm{j}\right) = \hat{\rho}_{\hat{\mathrm{y}}_\mathrm{i},\hat{\mathrm{y}}_\mathrm{j}} \sqrt{var\left(\hat{\mathrm{y}}_\mathrm{i}\right)\ var\left(\hat{\mathrm{y}}_\mathrm{j}\right)}, \\ \text{and } \hat{\rho}_{\hat{\mathrm{y}}_\mathrm{i},\hat{\mathrm{y}}_\mathrm{j}} = \text{estimated correlation between fractions } y_i \text{ and } y_j. \end{gathered} \tag{3.2}$$

The multiplicative error term ε_i of the nonlinear biomass function (Equation 3.2) implies an increasing variance with increasing covariate dimension. We quantified the resulting heteroscedasticity by parameterizing a power function with the model residuals over the fitted values. This function was then used to weight the residuals of the actual fit. Thus, neither the variances of the distinct biomass functions $var(\hat{y}_i)$ nor the combined model variance $var(\hat{\hat{y}}_i)$ showed heteroscedasticity.

In order to make the single model variances $var(\hat{y}_i)$ comparable to each other, to the variances of other biomass functions in the literature and to the combined model variances per tree species $var(\hat{\hat{y}}_i)$, dimensionless coefficients of variation for each model i were calculated (Equation 3.3),

Table 3.2: Tree layer specific parameters of the test site. Growth region: Middle German Trias High and Hill Land. Growth district: Göttingen Forest. Altitude: 340 m. hm: Height of stem of mean basal area. dm: Diameter of stem of mean basal area.

tree species	age	hm [m]	dm [cm]	stand volume [m^3 ha^{-1}]
European beech	76	23.3	27.6	164.0
European beech	20	14.9	11.2	4.8
ash	71	28.7	35.2	73.3
sycamore	76	24.3	23.6	18.7

where j is the index for the observed tree. These coefficients of variation were also calculated for the combined model error $v(\hat{\hat{y}}_i)$. $v(\hat{y}_i)$ and $v(\hat{\hat{y}}_i)$ thus represent the normalized deviation of the models. They are calculated as the quotient of the deviation and the estimated response. This normalization is advantageous since it scales every residuum by its expected dimension thereby making it easily interpretable and comparable. The absolute deviation would, due to the heteroscedasticity, increase with increasing dimension of the response y_{ij}.

$$v\left(\hat{\mathrm{y}}_{\mathrm{i}}\right) = \frac{1}{N_i - 1}\sqrt{\sum_{j=1}^{N_i}\left(\frac{\mathrm{y_{ij}} - \hat{\mathrm{y}}_{\mathrm{ij}}}{\hat{\mathrm{y}}_{\mathrm{ij}}}\right)^2} \tag{3.3}$$

where i denotes the fraction and j the observed tree. N_i is the number of observations in fraction i. The entire regression analysis was performed using with the R package *nlme* (Venables & Ripley, 2002). Additionally, we calculated the likelihood-ratio based pseudo-r-squared for each model using *MuMIn* (Barton, 2016).

To enable a comparison between the biomass functions for the different tree species 95 % confidence intervals were computed for European beech and oak using bootstrapping (DiCiccio & Efron, 1996). To do this every regression model for these two species was repeated 1,000 times using sub-samples of the original data which were selected randomly by drawing with replacement. In order to prevent the sample size influencing the width of the confidence intervals, the number of samples in every repetition matched the actual number of samples. All analyses were performed using the R software (R Core Team, 2016).

3.2.3 Sensitivity analysis

To analyze the behavior of our models, the biomass functions were applied on a real forest site. This site was chosen for testing purposes only. The trees of the site were not included in the regression analyses. The research site is located ca. 15 km east of the city of Göttingen. It is a mixed stand with European beech, sycamore and ash, which is typical for this region. The site is on a sun exposed slope with a stony substrate consisting of the products of limestone weathering overlain by a thin layer of loess (Table 3.2). It has a good nutrient and a good water supply.

Based on this test site, 5 simulated test sites, differing in their species composition, were generated. For this, the proportions of the 3 tree species in the real stand were modified using the *WaldPlaner* forest simulator (Hansen & Nagel, 2014). With this software we randomly cloned original trees from the test site until the target mix ratio was achieved.

3.2.4 Nutrient contents

To consider site sustainability is to ask the question - how to best manage the scarce nutrient resources available? To do this, the nutrient response efficiencies of the distinct species and fractions appear to be a reasonable (Henderson et al., 2012). The nutrient response efficiency (Vitousek, 1982) tells us how much carbon [kg] can be bound by a plant per 1 kg of applied nutrients. According to Vitousek (1982), we define the response efficiency as the inverse of the element concentration of the biomass. It is the ratio of carbon to the other mineral nutrients. The tree and fraction specific nutrient response efficiency of each nutrient is thus calculated by dividing the carbon concentration by the respective nutrient concentration in the tree fractions. It determines how much nutrient must be assimilated to grow a certain amount of biomass. Trees with high nutrient response efficiency need less nutrients to grow the same amount of biomass in the respective fraction than a plant with lower nutrient response efficiency. The total tree nutrient response efficiency was calculated by dividing the total tree concentration of carbon, the sum of all 4 fractions, by the total concentration of the respective nutrient. From the samples that were chemically tested, the average nutrient response efficiencies per tree species and were calculated. This was achieved by calculating the mean nutrient response efficiencies per tree species from the single-tree values.

3.3 Results

3.3.1 Biomass functions

The numbers of parameters in the biomass functions were determined by Akaike Information Criterion (AIC) Akaike (1981). By including tree height in the models for stem wood and bark the AIC scores were lowered markedly. This was observed for all species. In those cases, where tree height had a significant influence on the biomass, additional models were calculated with the dbh as the only independent variable. As a consequence of this, for each of the tree species there is an easily applicable dbh model available for each function. The coefficients of variation $v(\hat{\hat{y}}_i)$ and $v(\hat{y}_i)$ allowed a direct comparison of the single and the combined variances. In those cases in which the tree height coefficient was significant the model coefficients of variation were markedly reduced by its inclusion. The coefficients of variation fall into two groups (Table 3.3). The coefficients of variation for the functions of stem wood and bark of the stem wood are clearly smaller than those for branches and twigs. Even if the height is not included $v(\hat{y}_i)$ of the stem wood and bark models is substantially smaller than $v(\hat{y}_i)$ of the branches and twigs.

Altogether $v(\hat{y}_i)$ ranged from 0.02 to 0.28. With values between 0.03 and 0.04, the combined model coefficients of variation when collinearity is taken into account (Equation 3.2) were always small. The combined $v(\hat{\hat{y}}_i)$ were calculated from the respective best models (the models with height parameter for stem wood and bark). The combined model coefficients for the European beech, oak and ash models were very close to the coefficients for stem wood and stem wood bark. Although there were correlations between fractions, these were higher for models with low variance. Accordingly the combined model coefficients of variation for European beech, oak and ash were low. Only the sycamore model showed considerable difference between the combined model variation coefficients and the variation coefficients of stem wood and bark of the stem wood. This is explained by the relatively high correlation between the stem wood biomass with the branch and twig biomasses. Despite this, because the coefficients of variation for the sycamore stem wood and bark models are relatively low, the combined model coefficients of variation are approximately the same as those for European beech and oak. As the residuals of each model as well as all biases were not trending and each bias was near 0, it can be assumed that all models are valid. The highest relative bias found amounted only 1.8 % of the mean expectation.

A comparison of the biomass models should show whether separate biomass functions for sycamore and ash are necessary. For this purpose confidence intervals were generated for the European beech and oak functions (Figure 3.2). We chose the 2-parametric functions with dbh as only descriptive variable for the model comparison. For stem wood there was no overlap across the whole spectrum of dbh. The curves of the stem wood functions of the 4 tree species ran more or less

Table 3.3: Coefficients and standard deviation of the biomass functions (Equation 3.1) for the tree species European beech, oak, ash and sycamore including a combined model error (Equation 3.2) for each species. $v(\hat{y}_i)$: Coefficient of variation. r^2_{LR}: likelihood-ratio based pseudo-r-squared.

species	N	fraction	α	β	γ	AIC	$v(\hat{y}_i)$	r^2_{LR}
oak	41	combined model error					0.040	
		stem wood	-5.6509 (±0.354)	1.9222 (±0.102)	1.6316 (±0.211)	435.9	0.039	0.998
		bark	-6.3130 (±0.348)	1.7037 (±0.102)	1.5738 (±0.209)	310.3	0.039	0.997
		stem wood	-2.8992 (±0.205)	2.5924 (±0.057)		468.2	0.050	0.997
		bark	-3.6611 (±0.201)	2.3505 (±0.056)		340.7	0.049	0.995
		branch	-1.3987 (±0.332)	1.5827 (±0.114)		377.1	0.131	0.975
		twig	-3.1298 (±0.657)	1.6758 (±0.201)		307.9	0.201	0.891
beech	38	Combined model error					0.036	
		stem wood	-4.5238 (±0.393)	2.1778 (±0.088)	1.0373 (±0.196)	414.5	0.037	0.996
		bark	-6.0328 (±0.362)	1.9511 (±0.080)	0.9515 (±0.183)	221.1	0.035	0.995
		stem wood	-2.5687 (±0.193)	2.5852 (±0.056)		438.1	0.049	0.993
		bark	-4.2350 (±0.175)	2.3230 (±0.051)		242.2	0.043	0.992
		branch	-1.1673 (±0.340)	1.5580 (±0.110)		349.5	0.117	0.897
		twig	-3.4372 (±0.839)	1.6993 (±0.271)		282.5	0.283	0.802
ash	37	Combined model error					0.026	
		stem wood	-4.3728 (±0.157)	1.9730 (±0.050)	1.1765 (±0.092)	374.2	0.023	0.999
		bark	-6.8483 (±0.341)	1.9737 (±0.092)	1.2909 (±0.180)	256.8	0.032	0.997
		stem wood	-2.4182 (±0.189)	2.5144 (±0.053)		426.9	0.039	0.996
		bark	-4.3601 (±0.237)	2.4730 (±0.064)		289.4	0.045	0.994
		branch	-2.1015 (±0.286)	1.8858 (±0.087)		330.7	0.074	0.969
		twig	-3.3426 (±0.657)	1.6436 (±0.204)		242.0	0.174	0.857

Continued on next page

species	N	fraction	α	β	γ	AIC	$v(\hat{y}_i)$	r^2_{LR}
sycamore	25	Combined model error					0.039	
		stem wood	-4.1220	2.0364	0.9797	225.1	0.029	0.997
			(±0.274)	(±0.082)	(±0.163)			
		bark	-5.8308	1.8880	0.9918	118.2	0.030	0.996
			(±0.274)	(±0.083)	(±0.165)			
		stem wood	-2.4235	2.4461		249.5	0.046	0.992
			(±0.215)	(±0.064)				
		bark	-4.1984	2.3299		141.9	0.047	0.991
			(±0.212)	(±0.064)				
		branch	-3.5005	2.1777		211.7	0.160	0.916
			(±0.593)	(±0.190)				
		twig	-5.6275	2.3005		147.9	0.252	0.893
			(±0.932)	(±0.298)				

equidistant from one-another, with the European beech stem wood function lying above those of all other species. The lower confidence limit for the European beech stem wood function lay very near to the expected value. The European beech confidence interval had therefore no overlap with the other biomass functions. Although the oak stem wood function ran between the sycamore and ash functions, there was also no overlap with the other stem wood functions because the confidence intervals were comparatively narrow.

For the bark models there were also no areas of overlap between the graphs. The bark biomass functions could be separated into 2 groups. The graph of the sycamore bark biomass function ran very near to that of European beech. Due to the relatively large data pool and the small data variance, the confidence intervals for the European beech models were very narrow so, despite the proximity on the graph, there was no overlap with the sycamore function. The bark biomass functions for ash and oak lay almost twice as high on the graph as those of European beech and sycamore. The confidence interval of the oak function was much wider than the European beech confidence interval. The distance between the oak and ash functions is, however, so large that there was no overlap between the two.

The confidence intervals of the branch functions were altogether much wider than those of the stem wood and bark functions. The confidence interval of the European beech branch model enclosed the oak function and vice-versa. The sycamore function for branch biomass overlapped with the European beech confidence interval in the dbh range between 35 - 50 cm and with the oak function confidence interval in the range 30 - 45 cm. The graphs of the sycamore and ash branch biomass functions were, however, much steeper. Consequently there is a clear difference between the sycamore and ash branch models to the European beech and oak models.

The graphs of the 4 twig biomass models were indistinguishable over most of the value range. The confidence intervals of these functions were very asymmetric and even wider than the branch function confidence intervals. The confidence interval of the European beech function was the widest and enclosed all the other functions across the whole diameter range. The confidence interval of the oak function was slightly narrower and enclosed the European beech and sycamore functions from a dbh of ca. 40 cm and higher. The function graph of the sycamore function ran within the confidence intervals of both European beech and oak over much of the dbh value range. It was, however, much steeper than all other models. The graph of the ash function lies close under that of the European beech function. Consequently, the twig functions are mostly indistinguishable by means of the confidence interval analysis although their curvature is partially different.

The proportion of stem wood in the tree biomass increased disproportionately high with increasing dbh. For the oak functions the stem wood percentage increased sharply at first, from 56 % by dbh 10 cm to 68 % by dbh 20 cm. By dbh 60 cm the stem wood share of the biomass was

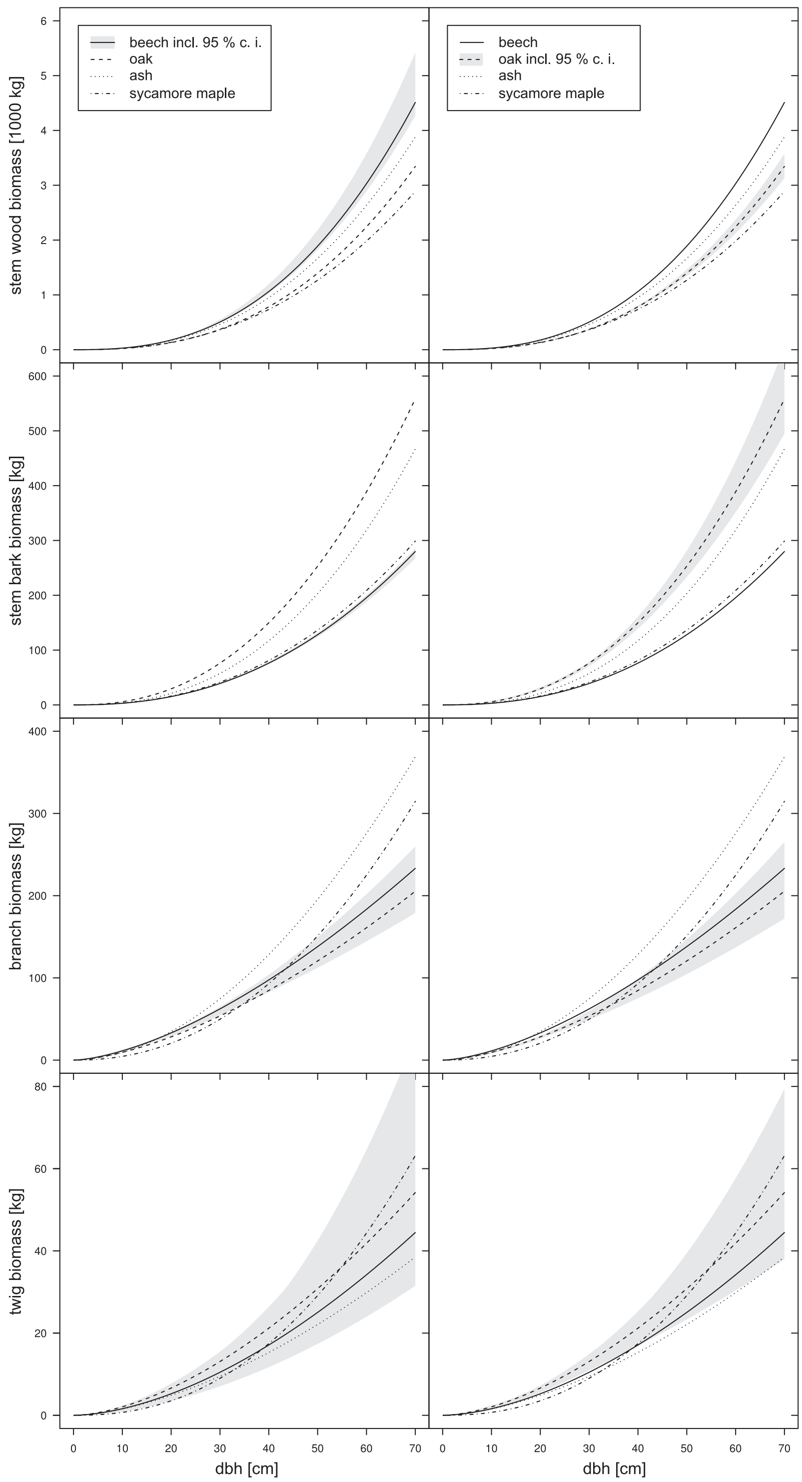

Figure 3.2: Regression of the biomass functions for European beech, oak, ash and sycamore over dbh. The left column includes a 95 % confidence interval for the European beech regression function. The right column shows the same regression functions including a 95 % confidence interval for the oak function.

79 % but did not increase much further after that. On average the stem wood share was 72 %. The proportion of the bark biomass was more or less constant at ca. 14 %. The share of branch as well as twig biomasses decreased with increasing dbh. The share reduced from 26 % to 5 % for branch and 4 % to 1 % for the twig biomass in the observed diameter range. The relationships between the tree fractions of the other tree species were comparable. The stem wood percentage for European beech increased from 78 % to 89 % in the diameter range 20 cm to 60 cm, that of sycamore from 77 % to 81 % and ash from 73 % to 81 %. For each tree species the stem wood share increases digressively and nears an asymptote. Above a dbh of ca. 60 cm the stem wood share in the tree species studied did not change much. The share of bark in the total biomass for European beech (6 %) sycamore (9 %), and ash (10 %) remained relatively constant. The share of biomasses in branches and twigs thus also decreased with increasing dbh for those 3 tree species.

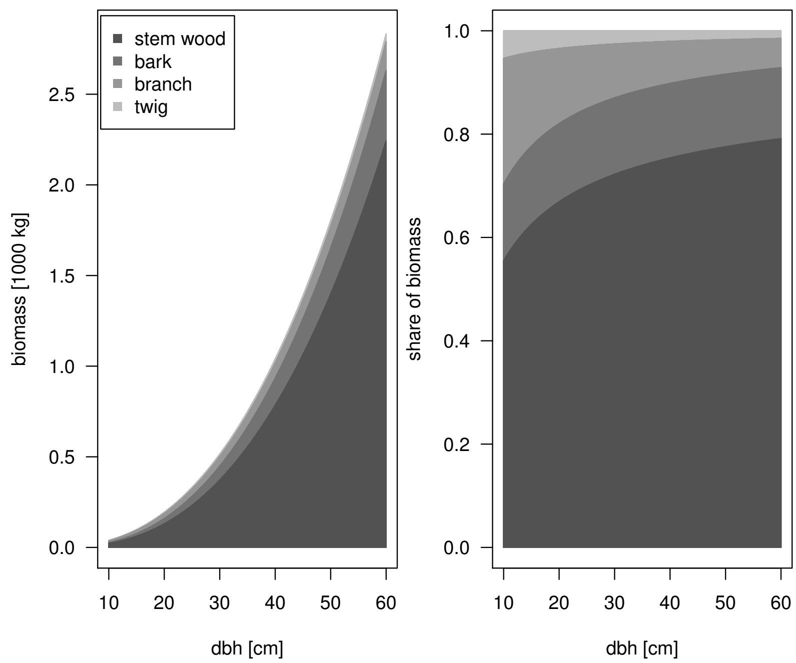

Figure 3.3: Biomass of the tree fractions in absolute scale (left) and relative to the total aboveground biomass (right) over dbh for oak.

3.3.2 Sensitivity analysis

In order to assess the magnitude of the effect that different biomass functions can have on results at the stand level, real and simulated test stands were used (Tables 3.2 and 3.4). The sum of the total aboveground biomasses for all trees in these stands was firstly calculated with the tree species specific biomass functions. Then, secondly, the sum of the total aboveground biomasses was again calculated using only the oak biomass functions for estimating biomasses of sycamore and ash trees. The full tree biomass at the stand level for the first test stand (proportion European beech: 75 %) was calculated to be ca. 200 t ha^{-1} when using tree specific biomass functions. Using oak biomass functions for sycamore and ash led to a 4 % overestimation of the stand biomass (ca. 7 t ha-1). The difference between the two calculation methods increased steadily with a decreasing proportion of European beech, reaching a maximum overestimation of 11 % (21 t ha^{-1}) for a stand with an equal tree species mixture. If the proportion of European beech was held constant, then

Table 3.4: Sum of total aboveground biomass on stand level for stands with differing share of species. The biomass is calculated with distinct tree species specific biomass functions and also with oak biomass functions for ash and sycamore.

share [%]			total aboveground biomass [t ha^{-1}]	
European beech	ash	sycamore	tree specific functions	oak functions for ash and sycamore
75	12	12	199.4	206.8
68	25	7*	201.6	208.6
68	16	16	199.0	210.1
68	7	25	194.5	206.9
50	25	25	197.3	213.1
33	33	33	188.1	208.8

*Original test site (Table 3.2)

the difference of the total aboveground biomass on stand level increased with a decreasing ash percentage in the stand. In every case the estimated total biomass at the stand level was lower when separate, species specific, biomass functions were used.

3.3.3 Nutrient contents

In our analysis, the nutrient contents differed particularly between the tree species. In order to examine significant differences, we performed a parametric one-way analysis of variance for each nutrient and fraction combination with 5 % significance level. The mean nutrients contents are listed in Table 3.5. All of the nutrient content data in the fraction and species groups were approximately normally distributed. For this, simple arithmetic group means are sufficient for data description and model building. This mean nutrients contents allows the tree and fraction specific calculation of the nutrients by multiplying its biomass with the respective element content from Table 3.5.

With ca. 500 g kg^{-1} (dry biomass) in stem wood, as well as in bark, carbon has the greatest share of any element content in the entire dry weight. The average carbon content lies between 475 g kg^{-1} and 509 g kg^{-1}, with slight differences between the tree species and fractions. In the stem wood sycamore differs significantly from beech while the carbon contents of other combinations do not differ significantly. In the bark fraction, ash and sycamore differ significantly from oak and beech. For sycamore and ash, the carbon content in the stem bark is a little lower than in the stem wood. The average nutrient contents, with the exception of a few calcium contents in the branches of sycamore and ash, were < 25 g kg-1. With few exceptions, the content of the various nutrients in wood can be ranked as follows: N $>$ K $>$ Ca $>$ Mg $>$ P $=$ S. Ash has the largest potassium content (1.65 g kg^{-1}) of all 4 tree species. The potassium content in ash is throughout significantly higher than in all other examined species. In terms of the magnesium content, the trees can be separated into two groups. The mean content is significantly higher for sycamore and European beech than for oak and ash. Generally, the nutrient contents in bark are between 3 (N, P and K) and 25 (Ca) times higher than in wood. The concentrations of nitrogen, phosphor and sulfur in sycamore bark are always significantly higher than those of European beech and than those in the bark of oak and ash. The bark of ash has significantly lower nitrogen concentrations than the other species but higher potassium content.

The nutrient response efficiency per tree species was calculated for the European beech - broad leaf mixed test stand (Table 3.2). In Figures 3.4 and 3.5, the results for the respective tree species and tree fractions are shown. The nutrient response efficiencies for stem wood usage were calculated by dividing the carbon concentrations in the fractions stem wood and bark by

Table 3.5: Group mean and standard deviation of nutrient content [g kg^{-1}] for the tree species European beech, oak, ash and sycamore. N: Observed number of trees.

spec.	frac.	Ca	Mg	K	C	N	P	S
oak N=8	stem wood	0.729 (±0.592)	0.100 (±0.090)	1.131 (±0.362)	495.898 (±6.515)	1.895 (±0.736)	0.087 (±0.060)	0.126 (±0.038)
	bark	26.350 (±6.787)	0.768 (±0.401)	2.363 (±0.789)	484.346 (±45.123)	6.518 (±1.602)	0.276 (±0.090)	0.622 (±0.237)
	branch	6.347 (±2.882)	0.522 (±0.169)	1.954 (±0.223)	492.667 (±5.918)	5.165 (±1.362)	0.323 (±0.091)	0.333 (±0.115)
	twig	7.368 (±2.727)	0.813 (±0.379)	3.050 (±0.395)	504.286 (±7.683)	10.531 (±1.285)	0.769 (±0.089)	0.621 (±0.103)
beech N=18	stem wood	0.968 (±0.156)	0.302 (±0.132)	1.135 (±0.248)	493.686 (±6.100)	1.492 (±0.520)	0.100 (±0.056)	0.091 (±0.016)
	bark	22.738 (±7.651)	0.517 (±0.191)	2.351 (±0.413)	487.684 (±22.248)	6.855 (±1.370)	0.351 (±0.093)	0.331 (±0.053)
	branch	3.150 (±1.536)	0.371 (±0.140)	1.559 (±0.309)	493.113 (±7.705)	2.805 (±0.520)	0.243 (±0.124)	0.148 (±0.019)
	twig	6.883 (±2.839)	0.524 (±0.266)	2.989 (±0.569)	508.817 (±8.408)	8.427 (±1.039)	0.791 (±0.297)	0.479 (±0.054)
ash N=37	stem wood	0.823 (±0.148)	0.193 (±0.08)	1.654 (±0.313)	493.495 (±5.497)	1.448 (±0.342)	0.092 (±0.036)	0.113 (±0.044)
	bark	25.505 (±7.428)	0.657 (±0.165)	5.067 (±1.397)	477.649 (±10.354)	5.312 (±0.644)	0.291 (±0.065)	0.469 (±0.071)
	branch	4.815 (±2.138)	0.319 (±0.079)	2.524 (±0.521)	492.675 (±5.58)	2.988 (±0.647)	0.228 (±0.075)	0.245 (±0.061)
	twig	8.691 (±1.689)	0.83 (±0.202)	6.344 (±0.775)	491.191 (±5.982)	8.359 (±1.175)	0.769 (±0.202)	0.73 (±0.091)
syca-more N=25	stem wood	1.068 (±0.26)	0.322 (±0.129)	1.403 (±0.268)	497.572 (±3.725)	1.467 (±0.186)	0.111 (±0.021)	0.118 (±0.021)
	bark	25.184 (±7.479)	0.861 (±0.21)	3.784 (±1.027)	474.982 (±10.544)	7.737 (±1.502)	0.57 (±0.144)	0.772 (±0.134)
	branch	4.089 (±1.673)	0.491 (±0.122)	2.394 (±0.335)	493.285 (±4.084)	3.403 (±0.654)	0.318 (±0.068)	0.283 (±0.059)
	twig	9.668 (±3.011)	0.815 (±0.227)	3.889 (±0.79)	495.799 (±6.299)	9.948 (±2.602)	0.898 (±0.268)	0.709 (±0.137)

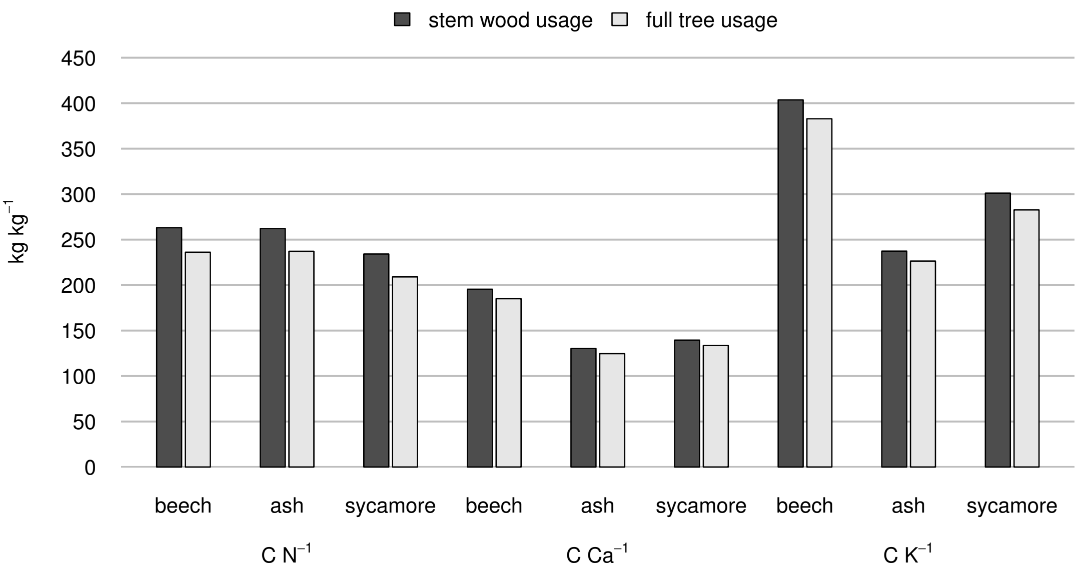

Figure 3.4: Nitrogen (N), calcium (Ca) and potassium (K) nutrient response efficiency for European beech, ash and sycamore when harvesting stem wood (including bark) only in comparison to a full tree usage.

the respective nutrient concentrations. Analogously, the nutrient response efficiencies for full tree usage were achieved by dividing the carbon concentrations of all 4 fractions by the particular nutrient concentrations. With reference to potassium, calcium and sulfur, European beech had the most efficient biomass production and, therefore, the most efficient carbon sequestration rate. Ash had the lowest nutrient efficiency for calcium and potassium, while phosphorus was used just as efficiently by ash as by European beech. With reference to magnesium, ash was the most efficient species and sycamore the least, while there was no real difference in efficiency between the 4 tree species with regard to nitrogen.

Because the branches and twigs are only used if the full tree is harvested, it seemed worth comparing the nutrient response efficiency of the stem wood biomass with that of the total aboveground biomass. The comparison revealed that the nutrient response efficiency of the total above ground biomass was always between 5 % and 10 % lower than that of the stem wood biomass. This trend can be observed for all examined tree species.

3.4 Discussion

3.4.1 Biomass functions

In comparison to other existing function types, such as those of Ledermann & Neumann (2006), Eckmüllner (2006) and Marklund (1988), the biomass model from Hochbichler et al. (2006) (Equation 3.1) proved, after extensive AIC and residual analyses, to be the most suitable. The model was fitted directly nonlinear without data transformation. There was thus no need for a subsequent bias correction (Baskerville, 1972; Smith, 1993). Due to the sufficiently large data pool the entire bandwidth of forestry relevant tree dimensions is covered by our biomass functions. A mixed effect regression model with distinct error structure for regional clusters did not improve our models. We therefore did not consider any mixed effect.

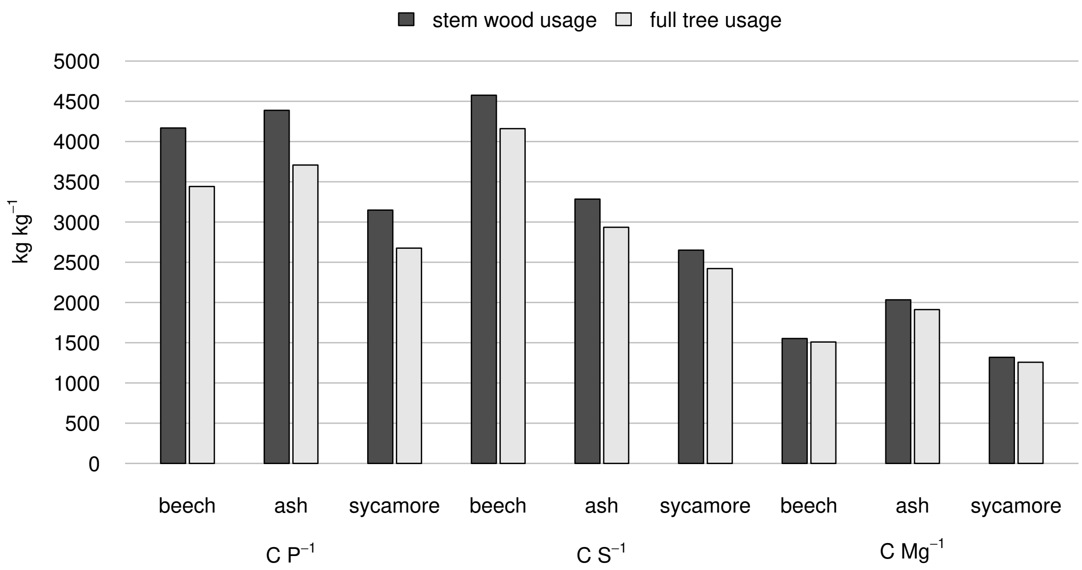

Figure 3.5: Phosphor (P), sulphur (S) and magnesium (Mg) nutrient response efficiency for European beech, ash and sycamore when harvesting stem wood (including bark) only in comparison to a full tree usage.

In large parts, the quality of the models depended on the tree fraction being examined (Table 3.3). The branch and twig models showed a higher variation in comparison with the stem wood and bark models. The accuracy of estimation of all stem wood and bark models could, though, be improved by including tree height in the models. If the appropriate data is available, then these more complex models are preferable. This was confirmed performing analysis of AIC, $v(\hat{y})$ and r^2_{LR} (Table 3.3).

The nonlinear pseudo-r-squared can be interpreted as the proportion of explained variation. There are, nevertheless, unlike the linear r-squared, several possibilities of calculating it (Magee, 1990). The likelihood-ratio pseudo-r-squared r^2_{LR} are thus often not directly comparable to the r-squared of other studies. It, however, becomes apparent that our r-squared are roughly in line with all r-squared found in literature (see e.g. Zianis et al. (2005) for a broad overview). In most other studies the r-squared of the stem and bark models amount at least to 0.9. The same appears for the branch and twig models. With values ranging from 0.6 to 0.8, the r-squared are much smaller.

Other studies (Ledermann & Neumann, 2006; Pretzsch et al., 2014) have shown that other variables could also improve model accuracy. Including tree height, tree height at crown base, crown width, tree age and a dummy code for forked tree lowered model standard error for the European beech biomass model by ca. 6 % and the oak model by ca. 13 %, when compared to the dbh-only model in a study of Ledermann & Neumann (2006). These results couldn´t be replicated in this study. Only tree age led, in a few cases, to a significant, though very small, model improvement. The age of individual trees is, however, seldom surveyed in the practice, so age was not further considered in creating the models. Hochbichler et al. (2006), who developed branch biomass functions for oak and European beech, observed a slight model improvement of the beech model when using the crown ratio as additional independent variable. We were not able to reproduce this result with our data. The crown ratio was not significant in any model. The same was found for the tree height to tree diameter ratio. As we collected our data in pure stands under standard regimes, the influence of the mixture and concurrence on the allometry, as it was e.g. observed by Pretzsch & Dieler (2012), could not be analysed.

Using a simple nonlinear regression for the tree fractions meant that any within-species correlation (collinearity) between fractions was not taken into account. This is of course a simplification. Since collinearity would have led to a huge difference between the distinct coefficients of variation and the combined coefficients of variation and we observed only minor differences (Table 3.3), it becomes clear that collinearity in the model had no considerably negative effect on any model. The combined model coefficients of variation were primarily influenced by the stem wood and bark models, variation in the branch and twig models had very little influence. There was thus only high correlation between fractions with comparatively low variation. The highest impact of collinearity was found for the sycamore biomass functions. The dimension of the combined coefficient of variation, however, was still very small. It can therefore be assumed that collinearity did not limit the validity of any model. Further analyses with simultaneous regression methods, such as a Seemingly Unrelated Regression (Henningsen & Hamann, 2007) or Restricted Regression, could establish whether the model error could be further reduced by considering collinearity during the regression. At any rate, the results of the analyses undertaken here indicate a valid estimation of the model parameters. Simultaneous methods could probably reduce the model variance significantly. Other studies, for instance Sanquetta et al. (2015), came to the same conclusion. Using tree growth data they were able to show that the parameter estimations were close to the results when using both separate and simultaneous estimations, whereas the variance, and with it the model efficiency, could be improved by using simultaneous methods.

Due to the relatively small variance in the raw data, the confidence intervals for the stem wood and stem wood bark functions were, as expected, narrower than the confidence intervals for the branch and twig models in the model comparison (Figure 3.2). Owing to the very wide confidence interval calculated for the European beech twig function, it is only for the twig models that the biomass functions of other species overlapped with the European beech confidence interval. Because of the relatively large scattering of the twig (see also Table 3.3), the sycamore and ash twig functions could be substituted by the European beech function. The curve of the sycamore function, however, differed markedly from the other function curves. It should also be noted, that the twig biomass makes up only a small proportion of the total biomass.

The functions were compared using the 2-parameter models, with dbh as the single covariate, revealing clear differences in the biomass models. Using 3-parameter models, with tree height included as an additional variable, would reveal at least the same model differences. The addition of other significant variables would narrow the confidence bands even further, due to the reduced variance (Table 3.3). In conclusion, the comparison of the biomass functions obviously underlines the need for separate sycamore and ash functions. The biomass functions of these species differ clearly from the beech and oak functions. The estimation of single tree biomass for sycamore and ash using biomass functions for other tree species, which up to now has been the norm, certainly leads to biomass estimation errors.

The proportion of stem wood increases with increasing dbh (Figure 3.3). This increase in the stem wood proportion with increasing dbh could also be documented for European beech in the diameter range 6 - 16 cm by Grote et al. (2003). They observed an increase of the average stem wood proportion from 30 % to 80 %, which is very close to the results from this study (Figure 3.3) for that diameter range. The data used by Grote et al. (2003) were sampled in a mixed oak - pine stand, which indicates that the relationship of stem wood biomass is similar in these stands, at least in the diameter range 6 - 16 cm. Konopka et al. (2015) also recorded an increase in the stem volume of young European beech up to 4 cm dbh, while Cienciala et al. (2005) and Pretzsch et al. (2014) observed a stem wood share between 70 % and 90 %, with a mean of 82 %. This mean share is also similar to the data from this study (Figure 3.3), though neither of these 2 studies found a significant diameter trend. Genet et al. (2011) observed a shifting of the stem wood share from 60 % to 75 % in trees between 13 and 81 years old, which is also consistent with the results of this study. The stem wood bark percentage from our study of 6 % is consistent with all values found in the literature (Altherr et al., 1978; Grote et al., 2003; Pretzsch et al., 2014). The fraction proportions of oak also showed a diameter trend. The stem wood proportion has a rising tendency, but lies clearly under the stem wood proportion of European beech. The stem wood percentage of 68 % to 80 % in the 20 cm to 60 cm diameter range corresponds well with the data from Pretzsch et al. (2014), who observed a mean percentage of 75 %. Grote et al. (2003) observed an increase of the stem wood percentage from 61 % to 71 % in the dbh range 10 cm to 30 cm, which is again very close to the results presented here. The bark proportion is also consistent with the literature values (Altherr et al., 1978; Pretzsch et al., 2014), whereby Altherr et al. (1978) found a site dependency. Comparison of the fractions relations of ash and sycamore with literature functions were, due to differing fractionations, not possible. Comparison of the total aboveground biomass reinforces the validity as well as the importance of our models. It could be seen that our functions were slightly different to all other models found in the literature (Albert et al., 2014; Alberti et al., 2005; Bunce, 1968). As an example, our ash as well as our sycamore functions lay in between the functions of Albert et al. (2014), who parameterized distinct functions with trees from a rich and a poor coppice stand. Although there are differences in the parameter estimations between the new parameterized functions in our study to former studies, the general proportions seem to be consistent with other biomass functions for all 4 tree species. This was expected as biomass functions are known to have regional differences (Cerny, 1990; Thurnher et al., 2013). Publishing specific biomass function for the northern and central part of Germany seems thus to be worthwhile for all 4 species.

3.4.2 Sensitivity analysis

Biomass of ash and sycamore must recently be estimated by biomass function of other species. To assess the magnitude of the effect these false estimations can have on biomass estimations in the praxis, test stands were generated (Tables 3.2 and 3.4). The oak biomass function was preferred to the European beech function for these analyses, because the curve of the oak function was a better fit with the sycamore and ash function curves (Figure 3.2). The results reinforce the need for separate biomass functions. As observed before, especially the sycamore functions were different to the oak biomass functions. In particular for sycamore the estimate was substantially improved with a separate species specific biomass function. In stands with a high proportion of sycamore, estimating biomass using oak functions led to massive overestimation of the biomass and the sequestered carbon (Table 3.4). The same effect would also be evident in the products of forestry use and the downstream transport chain. The actual biomass potential would be considerably lower than the predicted potential. With respect to the fact that accurate biomass predictions are mandatory for a reliable biomass potential estimation, this underestimation, as it was obligatory until now, seems not to be acceptable.

3.4.3 Nutrient contents

Varying nutrient contents, not only between tree species but also between tree fractions, has been demonstrated in many studies for European beech and oak before (e.g. Augusto et al. (2000); Müller-Using & Rademacher (2004); Pretzsch et al. (2014)). In this study these differences in nutrient content were also shown for sycamore and ash (Table 3.5). In comparison to European beech and oak, ash and sycamore species have significantly higher calcium and potassium contents and significantly less carbon contents. Export of sycamore and ash biomass will thus be underestimated, if European beech or oak contents are used for their estimation. In other studies (e.g. Joosten & Schulte (2003)), it was shown that nutrient contents also significantly depended on the site quality. As sycamore and ash only grow on sites of relatively high quality, our sample for the chemical analysis comprised rich stands only. The stand quality thus had of course no significant explanatory content in our study. The nutrient contents are generally higher in the bark than in the wood and this applies to all 4 studied tree species. Because the proportion of bark within a tree decreases with increasing branch diameter, small diameter wood fractions (branches and twigs) have higher nutrient concentrations.

This is reflected in lower nutrient response efficiencies for these fractions Vitousek (1982); Rumpf et al. (2011); Meiwes et al. (2012). A greater amount of nutrients has been used in building biomass in these smaller fractions than are needed to build the same biomass in stem wood. Except for nitrogen, the calculated nutrient response efficiencies were substantially different for the observed tree species. This again reinforces the need for distinct biomass and nutrient content models. It must, however, be considered that our definition of the nutrient efficiency is slightly different to the original definition by Vitousek (1982). He stated that in long-living perennial plants the nutrient efficiency calculates as the inverse of the nutrient concentration in the wood increment, the litterfall and the root turnover. As none of those variables was measured in our study and because the litterfall as well as the root turnover remain in the stand, their efficiency is not relevant for the calculation of the biomass potential. We thus only focused on the nutrient content of the aboveground biomass. The use of small dimensioned wood leads to a disproportionately high nutrient loss and has a greater negative effect on the nutrient supply of the site than stem wood harvest alone (Block et al., 2013; Meiwes et al., 2012; Pretzsch et al., 2014). On the other hand, in times of modern processing methods, in precisely those recently often unused wood fractions there is a huge potential for the bio-based industry.

3.5 Conclusions

When coupled with individual site information, the results of this study help determining the optimal biomass potential of mixed stands with European beech, oak, sycamore and ash. In forest stands with homogeneous tree species and age distributions the biomass and nutrient quantities could certainly be estimated with sufficient accuracy using stand parameters such as mean basal tree area (Pretzsch et al., 2014). As is made clear by the example in Table 3.4, this is not possible in mixed broadleaf stands. The use of the oak biomass function for all tree species would lead to overestimating both biomass and nutrient quantities. Because the share of multiple layer, species-rich stands in forests is increasing (TI, 2014), and will probably continue to increase (BMEL, 2014a), the need for species specific biomass functions becomes ever more urgent. For estimating the optimal site specific harvest quantities, biomass functions, and knowledge of tree fraction nutrient content, for the tree species sycamore and ash are a useful addition to already existing functions, and could help to enable the full biomass potential of the forest to be exploited in the future. They improve the planning security of forestry activities and of all further processes in the biomass supply chain and help to analyse the trade-off between usage intensity and site sustainability. All further analyses that require reliable biomass estimations, for example supply analysis for operative and strategic planning or carbon inventories, will also profit from the biomass functions introduced here. The introduced models can help gathering the huge biomass potential from long-term broadleaf stands that was unused till now (TI, 2014).

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Chapter 4

Modelling the economically viable wood in the crown of European beech trees

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Abstract

Long-term forest development programs in Germany aim on an increase of close-to-nature broadleaf forest stands. This means that the economic importance of European beech is expected to increase. The economic potential of a tree basically consists of the stem as well as the economically viable wood volume in the crown. Due to the high morphological variability of European beech crowns, taper models are often not satisfactory for predicting the economically viable wood volume arising from crowns. Prediction models with a higher precision are recently still lacking. Aim of this study is thus the development of prediction model for the economically viable crown wood volume of European beech trees.

We determined the distribution of the wood volume in the crown over the branch diameters using the multistage *randomized branch sampling* method (RBS). The tree-specific wood volume distribution on the branch diameters were used to cluster all sampled trees into 3 groups. Additionally, we developed a method able to distinguish between economically viable and unviable crown branches. Basing on the RBS measurements as well as revenues and processing costs, we modeled the economically viable wood volume from the crown for each tree. To calculate the wood volume under bark, we parameterized a bark thickness function from disk samples of the trees.

We showed that the European beech crowns could be clustered into 3 groups differing in their wood volume distribution. The economically viable wood volume in the crown significantly depended on this grouping parameter as well as diameter at breast height (DBH). By contrast, the total amount of wood in the crown only depended on DBH. The differing viable wood volumes in the crowns were thus explained by different wood distributions and not by differing total crown wood volume. To make the results applicable in practice forestry, the modeling results were used to develop a regression formula able to predict the economically viable wood volume in the crown depending on the DBH and the crown type. As the crown type can also be predicted via measurable tree covariates, the regression model of the viable wood volume in the crown can be used as a support tool for the management of European beech stands. Sensitivity analysis quantifies how harvest revenues and costs translate into different viable tree volume.

Keywords

Economically optimal wood cut, Crown morphology, European beech, viable crown wood, wood allocation, forest management

Highlights

- Morphological measurements of 163 European beech tree crowns via *RBS* method.
- Distinguishing the economically viable from the whole crown wood.
- Categorization of European beech crowns into morphological types.
- Development of a viable crown timber prediction model for forest management.

4.1 Introduction

Although European beech (*Fagus sylvatica* [L.]) forests have been identified as the dominant forest communities in the potential natural vegetation of Germany (FANC, 2010), with 1,680,072 ha, they currently only account for 15 % of Germany's forest stand cover (TI, 2014). Long-term ecological forest development programs result in a general increase in deciduous tree species with a focus on

European beech (MFACP, 2004). The economic importance of European beech will thus further increase.

Traditionally the objective of European beech management is to maximize valuable stem wood (Nagel & Spellmann, 2008). Especially under the perspective of modern utilization methods like bio-economics (Hildebrandt et al., 2014) and the increasing demand for fuel wood (Mantau, 2012), the economic importance of smaller branches of European beech is expected to increase. Thus a large proportion of the economic potential lies in smaller branches. Under certain conditions, further economic potential can be found in the tree stump and foliage (Miettinen et al., 2014). For a suitable management of European beech stands, it is necessary to assess the economically viable wood cut fully (Möhring, 1997). Therefore, as well as predicting the wood from the sympodial stem, it is also necessary to predict the economically viable wood cut in the sympodial crown. In the complex crowns of broadleaf trees, the economically viable wood can be substantially smaller than the whole wood volume. For this purpose, a model able to distinguish the economically viable wood volume from the whole wood volume in the crown is needed. For the stem volume prediction, there are many different and sophisticated tariff and other functions available. Cubic taper models exist, providing an adequate prediction of the economic potential of coniferous trees and the stems of deciduous trees (Kuzelka & Marusak, 2012). However, those taper functions do not account for the complex sympodial form above the crown base of broadleaf tree species where the wood volume is not allocated around a throughout stem axis. They are therefore imprecise in predicting the wood volume arising above the crown base. They are usually calibrated for a minimum small-end diameter threshold of 7 cm. This small-end diameter can lack economic interpretation.

The aim of this study is to develop a parametric, practically usable prediction model of the economically viable wood volume in the crown of European beech trees. For this purpose, 163 beech trees were felled. Using the multistage *Randomized Branch Sampling* (RBS) method (Gaffrey & Saborowski, 1999), a sound sample of branches was measured from each tree. The measurements were taken to examine the tree individual distribution of the wood volume in the crown on the crown branches. To develop tree individual morphological covariates, the sampled trees were clustered into groups with differing wood volume distribution. A multinomial regression model enables the prediction of this covariate via measurable tree attributes. We additionally developed a model, which predicts the viable wood volume from the measured wood volume distribution. This viable wood volume does not depend on freely selected but on economically justified small-end diameters. We developed a method to classify economically viable and unviable branches in European beech crowns via a break-even analysis. Then only the wood volumes of viable branches were estimated via RBS. The modeled economically viable wood volume thus depends on the size of the tree and the volume distribution in the crown. To calculate the wood volume under bark, we parameterized a new bark thickness function from disk samples of the trees. To make the results applicable in forest practice, we performed a regression analysis with the modeled economically viable wood volume and further tree covariates. To ensure the applicability, we only used practically measurable tree attributes. The regression model represents a new approach for modeling the economic potential of European beech crowns and therefore a novel decision support tool for forest management operations.

4.2 Materials and Methods

The dataset for this study comprised measurements from a destructive sample of 163 European beech trees sampled using the multistage RBS method (Gaffrey & Saborowski, 1999; Jessen, 1955). These data were compiled from 2 existing databases at the Northwest German Forest Research Station and the Baden-Württemberg Forest Research Centre.

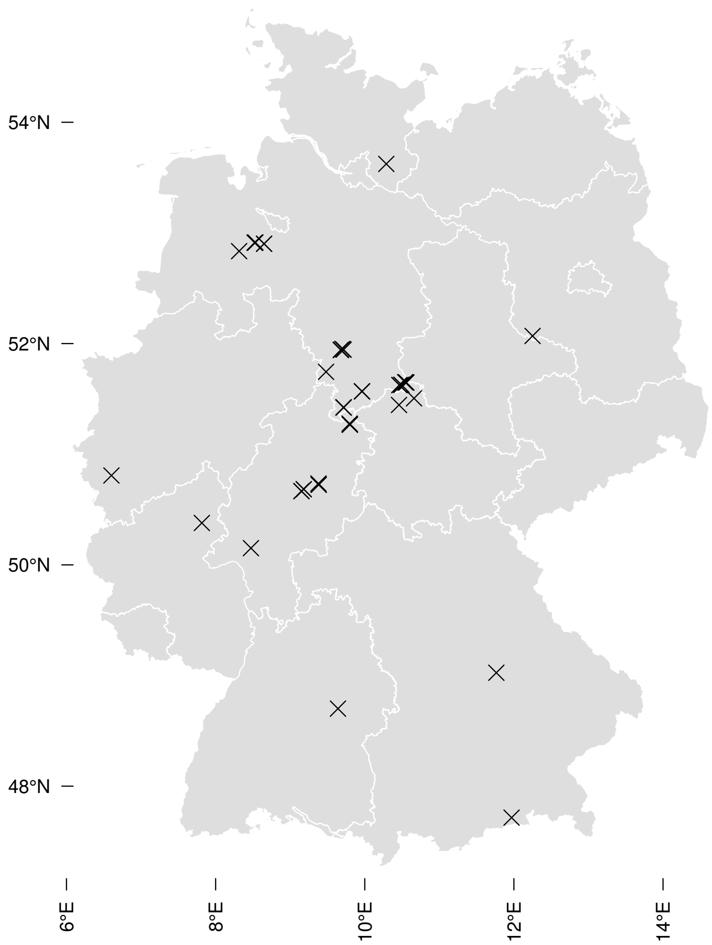

Figure 4.1: Sample site locations. Source of the background map: FACG (2014).

4.2.1 Selection of trees

The data were collected during 2009 and 2014. Altogether 163 trees were destructively sampled. In order to cover as many growth zones as possible, the sample plots were distributed throughout Germany (Figure 4.1). To ensure representation of the entire relevant diameter range, we chose up to 3 forest sites with different stand ages within these growth zones. All selected sites were high forests under standard management regimes. Depending on the area size of the plot, 2 - 4 sample trees were selected. In addition to the morphological measurements via RBS, DBH and tree height were measured (Table 4.1).

4.2.2 Selection of disks

To subtract bark from the wood volume, stem and branch disks for bark thickness measurement were taken from 37 trees of the NW-FVA study (Table 4.2). Up to 6 disks were randomly selected using the importance sampling method (Gregoire & Valentine, 2008). The proxy function, which is necessary for calculation of the sampling probability, was derived by the volume distribution of the branch diameters over the approximated tree height (which were both measured for volume

Table 4.1: Summary statistics of the sampled trees. The sample size was 163.

	DBH [cm]	height [m]	age [a]
min	8.0	13.1	21
mean	35.4	25.3	85
median	34.8	26.0	80
max	78.3	38.5	180

Table 4.2: Summary statistics of disks for bark thickness measurements.

	single bark thickness [mm]				disk diameter over bark [cm]			
N	min	mean	median	max	min	mean	median	max
149	0.6	3.0	2.4	9.0	1.0	18.0	12.0	64.2

estimation via RBS anyway). The selection probability of the disks was thus proportional to their disk diameter. Diameter and the bark thickness of the disks were measured at 4 directions of the selected disks directly after extraction.

4.2.3 Selection of branches

The estimation of the wood volume in the crown was based on the RBS method of multistage probability sampling. RBS is an unbiased method of probability sampling used for estimating specific tree parameters by measurable auxiliary variables (Jessen, 1955; Gaffrey & Saborowski, 1999). In our application, RBS enables estimation of the wood volume in the crown or in specific parts of the crown by measuring only a sample of branch segments instead of measuring all branch segments in the crown. Only relatively few measurements of branch diameters and branch segment lengths have to be taken for an accurate estimate of the whole wood volume in the crown or the wood volume of specific crown parts.

RBS is based on the knowledge of the conditional probability q_{lj} of choosing the j-th out of n *branches* at a *node* l in the crown instead of choosing another branch of this node. The probability q_{lj} can be calculated by an auxiliary variable instead of the (complicated measurable) target variable itself (Gregoire et al., 1995; Gregoire & Valentine, 2008; Valentine et al., 1984). Instead of measuring the volume of all branches at a node, in our case, we only had to measure the base diameters d_{lj} of the branches to calculate q_{lj} and the volume of one branch. As West (1999) examined an allometric coefficient of 2.67 between branch volume and branch base diameter, the branch base diameter to the power of 2.67 is expected to provide efficient estimates. In our study, the conditional probability has been selected to be

$$q_{lj}(d) = d_{lj}^{2.67} / \sum_{j=1}^{n_l} d_{lj}^{2.67} \tag{4.1}$$

Thus once all branch base diameters d_{li} at a node were recorded, one of the branches can be randomly chosen with probability q_{lj}. Only the *segment* volume of this chosen branch has to be measured, where a *segment* is defined as the part of the branch between 2 nodes (Gregoire & Valentine, 2008). We chose the formula for a conical frustum (Equation 4.2) to calculate the segment volume v_{lj} via the branch base diameter d_{lj}, the base diameter at the following node d_{lj+1} and the segment length h_{lj}. The volume of the following node d_{lj+1} was also measured and added to the segment volume v_{lj}.

$$v_{lj} = \frac{h_{lj}\pi}{12}\left(d_{lj}^2 + d_{lj}d_{lj+1} + d_{lj+1}^2\right) \tag{4.2}$$

The crown base, which is the height where the throughout stem ends and the sympodial crown starts, represented the first node of the RBS procedure. To have a measurable criterion, we defined the crown base to be the tree height where a branch base diameter was $> 1/5$ of the stem diameter at that height. A whole RBS path thus consisted of a succession of randomly selected branch segments from the crown base up to one shoot bud. Along the path all branch base diameters and all segment volumes were measured. In order to get an idea of the variation, 3 random and distinct RBS paths were obtained for each of the 163 sampled trees.

4.2.4 Estimation of wood volume in the stem and in the crown

The calculation method for the point estimates of the volumes as well as for the estimated variance is described in the literature (e. g. Gregoire & Valentine, 2008). The stem form was assessed by section-wise diameter measurements at certain tree heights up to the crown base. The sum of these section volumes, also calculated by the conical frustum formula (Equation 2), gave the whole stem volume from the ground up to the crown base.

4.2.5 Economically viable wood volume in the crown

Crown type differentiation

To calculate the volume distribution according to the branch diameters in individual tree crowns, the cumulative wood volume amount $\hat{V}_i(d)$ in the crown was calculated from the crown base up to each recorded branch base diameter (d) along each RBS path. This distribution was normalized by dividing the predicted cumulative crown volume below $\hat{V}_i(d)$ [m3] by the whole wood volume from the crown $\hat{V}_i(0)$ [m3] (Equation 4.3) and by dividing the base diameter of every branch d_{ij} by the maximum diameter found d_{max}. $F(d)$ thus denotes the wood volume amount over branch diameter in the crown.

$$F\left(d\right) = \frac{\widehat{V}_i\left(d\right)}{\widehat{V}} \tag{4.3}$$

The diameter where half of the wood volume amount was located above (below respectively) was interpreted as the median branch diameter of a tree crown. This median volume branch diameter $F(d_{0.5})$ was easily interpolated from the generated diameter distribution for every RBS path, where $d_{0.5}$ denotes the branch diameter for which $F(d_{0.5}) = 0.5 * F(d_{max})$. The same appears for the lower $F(d_{0.25})$ and upper quantile $F(d_{0.75})$. The curve trend of $F(d)$ over branch diameter thus indicates whether most of the wood volume is located in relatively small or in larger branches. Generally, there were 3 types of volume distribution in the data (Figure 4.2). The first type showed a high share of volume in relatively small branch dimensions (left). The median branch diameter of these trees was close to the lower quantile. In the balanced type (center), half of the wood volume was found above a branch diameter that was approximately half the size of the largest diameter of the respective tree. In the third type (right), major part of wood volume was allocated in the larger branch diameter range. The median diameter was close to the upper quantile.

As there were 3 paths per tree, the tree individual median diameter was calculated by the median of the 3 median branch diameters. The lower and upper quartiles were created in the same way. We thus generated 3 tree individual continuous variables. These enabled a clustering of the trees into 3 crown types which differ in their wood volume amount. As the crown types based on the volume distribution in the crowns, they should represent groups with different economically viable wood volumes. We chose the *k-means* cluster algorithm (R Core Team, 2016), which minimizes

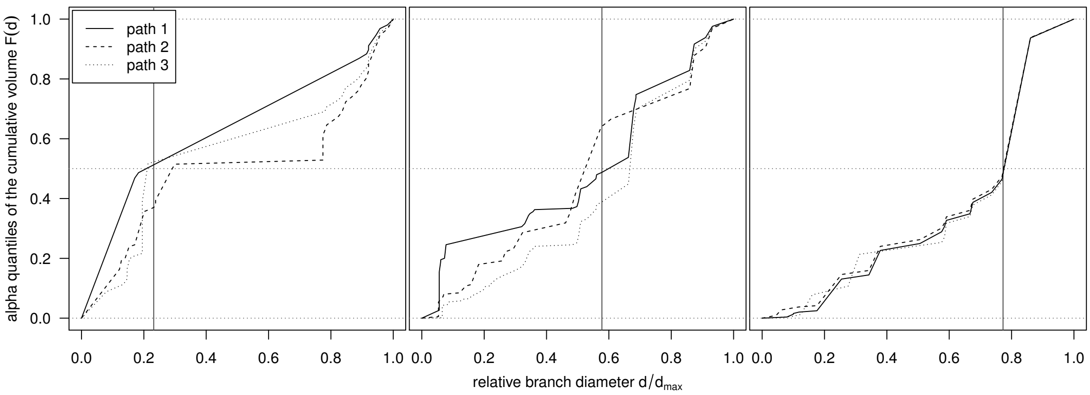

Figure 4.2: Cumulative crown wood volume over relative branch diameter for 3 exemplary trees. For each tree all 3 RBS paths are displayed. The diameters where half of the timber volume is located above, respective below (the median relative branch diameter) are marked by vertical lines.

the within-cluster Euclidean distance among observations and group means by the sum-of-squares method (Wagstaff et al., 2001), to cluster the data into 3 morphological crown types.

The median tree diameter as well as the quantile tree diameters are not measurable in practice. To differentiate a beach crown into 1 of the 3 mentioned groups in forest management, it is thus necessary to predict the crown type by other tree attributes. A multinomial logistic regression method (Hutcheson & Moutinho, 2008) was parameterized to predict the crown type clusters from practically measurable morphological tree variables x_i (equation 4). In this case, the x_i are the DBH, the tree height, the tree height at crown base and the ratio of the base diameters at crown base. The ratios of the branch diameters at crown base were calculated by dividing the 2nd largest base diameter at the crown base by the respective largest branch diameter.

We fitted a log odd model with $J = 3$ categories to a probability function which predicts the probability that an individual tree is belonging to a crown type category j rather than to the reference category $j^{'} = 1$ by $i = 4$ variables.

$$\log\left(\frac{P\left(Y=j\right)}{P\left(Y=j'\right)}\right) = \beta_{j0} + \beta_{j1}x_1 + \beta_{j2}x_2 + \cdots + \beta_{ji}x_i \tag{4.4}$$

The probability of an individual to belong to group j in relation to the reference is therefore calculated as

$$P\left(Y=j\right) = \frac{\exp\left(\beta_0 + \beta_{j1}x_1 + \beta_{j2}x_2 + \cdots + \beta_{jk}x_k\right)}{1 + \exp\left(\beta_0 + \beta_{j1}x_1 + \beta_{j2}x_2 + \cdots + \beta_{jk}x_k\right)} = \frac{exp(\boldsymbol{x}_i^{'}\boldsymbol{\beta}_j)}{1 + exp(\boldsymbol{x}_i^{'}\boldsymbol{\beta}_j)}$$

and the probability of an individual to belong to group j considering all groups calculates as

$$P\left(Y=j\right) = \frac{exp(\boldsymbol{x}_i^{'}\boldsymbol{\beta}_j)}{1 + \sum_{s=1,s\neq j'}^{J} exp(\boldsymbol{x}_i^{'}\boldsymbol{\beta}_s)}$$

where crown type 1 represented the reference category $j^{'}$. The model was fitted with the R package *NNET* (Venables & Ripley, 2002). The significance of a variable was examined by linear discriminant analysis. For model quality testing we predicted the crown type with our model and compared the result with the actual crown classification by the k-means analysis. This classification was performed by a leave-one-out cross-validation (R package *MASS*; Venables & Ripley, 2002) and an in-sample reclassification.

Modelling the economically viable wood volume in the crown

As biasedness of the point and the variance estimate do not depend on the number of stages, RBS also allows the volume estimation of specific parts in the crown (Cancino & Saborowski, 2005). We used this property to estimate the tree individual viable wood volume in the crown only. For this, we programmed a model that distinguished the economically viable from economically unviable branches in the RBS sample (Algorithm 4.1). After running the algorithm, only the economically viable branches were then used to estimate the wood volume via the RBS method. The predicted wood volume after application of the separation algorithm thus reflected the economically viable wood volume in the crown.

To distinguish viable from unviable branches, each RBS node and subsequent selected branch segment were aggregated into one *branch structure*. In the event that many nodes occurred in close succession (no branch segments in between), they were regarded as one large node and aggregated with the following node and branch segment to form a large branch structure.

Each of the branch structures were then, starting at the crown base, successively rated in terms of revenue and cost. The revenue was calculated by multiplying wood volume [m^3] (under bark) by timber price [€m^{-3}]. The cost associated with any one branch structure was assumed to be constant per processing step and was interpreted as marginal cost (Möhring, 1997) of processing this branch structure. Whenever a branch structure had a positive marginal return, it was additionally proofed if the former branch structure was viable. If this was the case, the branch structure was labeled to be economically viable. A branch segment is thus only considered as economically viable if its piece-volume is large enough to have a positive marginal return. If a former branch structure was unviable, the processing costs doubled, because the continuation of processing thereafter would require an additional cut. Each RBS path of every crown thus had a specific break-even point (Starr & Tapiero, 1975) after which further processing would result in lower marginal returns. The small-end diameter of this last viable branch structure was recorded. The model was programmed in the statistical programming language R (R Core Team, 2016).

After neglecting the unviable branch structures, the tree individual viable wood volume from the crown as well as the variance were estimated by means of RBS. The final small-end diameter of an individual tree was defined as the mean of the end diameter of all 3 paths.

The model (Algorithm 4.1) thus needed timber price [€ m^{-3}] (under bark) and marginal costs [€ processing step^{-1}] as input parameters. It was parameterized with commonly used values to ensure realistic results. The revenue was set to 50 € m^{-3} (under bark) to reflect the common price for industrial wood in Germany in 2016 (Degenhard, 2016). The fixed cost parameter was based on the European beech wages table from the forest entrepreneurs association (Haarhaus, 2012), which assumes an 125 % entrepreneur fee and 19 % value added tax. Based on the assumptions that each node occurring represented one processing step and that the costs of each were constant, the costs amounted to 0.35 € processing step^{-1}. The model outputs were the economically viable wood from the crown (under bark) [m^3] and small-end diameter [mm].

$$\begin{aligned} y &= \beta \prod_{i=1}^{k} x_i^{\alpha_i} \\ \leftrightarrow \log(y) &= \log(\beta) + \sum_{i=1}^{k} \alpha_i \log(x_i) \end{aligned} \tag{4.5}$$

The modeled viable wood volumes were used to parameterize an allometric growth model (Equation 4.5) with k covariates. This parametric regression model allows forecasting of the economically viable crown wood volume by measurable covariates and is therefore easily applicable in forest man-

```
initialization of processing costs and revenue by the user
aggregation of the RBS knots and branch segments into structures

for i in (1 : N_paths) do
    for j in (1 : N_structures) do
        if volume of structure_ij * revenue > processing costs then
            if economical viability of structure_ij-1 == TRUE then
                economical viability of structure_ij ← TRUE
                small − end diameter_j ← end diameter of structure_ij
            else
                if volume of structure_ij * revenue > processing costs * 2 then
                    economical viability of structure_ij ← TRUE
                    small − end diameter_j ← end diameter of structure_ij
                else
                    economical viability of structure_ij ← FALSE
                end
            end
        else
            economical viability of structure_ij ← FALSE
        end
    end
end

crown timber volume ← RBS estimation of the viable structures
variance ← RBS estimation of the viable structures
small-end diameter ← mean(small-end diameter_1, ..., small-end diameter_N_paths)

return (crown timber volume, variance, small-end diameter)
```

Algorithm 4.1: Pseudocode of the of the economically viable wood volume distinguishing model where N_{paths} is the number of paths per tree (in this study always 3) and $N_{structures}$ is the number of branch structures per path.

agement. For this purpose, sets of results, differing in their parameterization of input variables, were generated with the viable wood volume prediction model (Algorithm 4.1). The revenue as well as the cost input parameters were firstly set to the common parameter combination (50 € m^{-3}, 0.35 € $step^{-1}$) and then separately changed by 20 %. Altogether, there were 9 result sets generated where each set of results involved 163 datasets. Because there were void datasets, whenever the algorithm assigned no viable wood volume in the crown, the data reduced to 1347 datasets. The regression analysis was composed of the covariates DBH, tree height, tree height at crown base, crown width, diameter ration at crown base and tree age as well as crown type, revenue scenario and cost scenario, which both functioned as dummy variable. The dependent variable was the modeled economically viable wood volume in the crown. The significance analysis and the model parameterization were performed by a *generalized linear model* (R Package *stats*; R Core Team, 2016). Proof of the significant impact of the covariates on α was not possible due to insufficient crown type 3 observations in larger DBH dimensions. The significance analysis was thus performed on β. Linearity and homoscedasticity were achieved by a Gamma distributed log-link function (Wood, 2006).

Table 4.3: Summary statistics of the linear double bark thickness [mm] regression model. Independent variable is the diameter over bark [cm] (fresh).

variable	coefficient	standard error	t-value	p-value
intercept	1.87804	0.25	7.42	<2*10-16
diameter	0.23253	0.01	16.06	<2*10-16
observations	149			
AIC	565.0			
model range [cm]	0 - 65			

4.2.6 Allometric relationships

In the metabolic scaling theory, the relationship between two plant organs (y and x, see also Equation 4.5) can be described by a power law (Huxley, 1932; Niklas, 1994). This power law interprets the intraspecific relationship between plant organs for a given species. The variability of the relationship describes the strength of the allometry (Pretzsch, 2010; West et al., 1997). Allometric model are thus useful to investigate the relationship between variables of economic interest and further tree attributes.

To consider the assumption of allometric regressions (Stumpf & Porter, 2012), we transformed the data by taking the natural logarithm. The relationships were regressed with the *standardized major axis* method (R package *SMATR*; Warton et al., 2012). The retransformation bias was estimated and corrected from the residual standard error of the log linear model (Sprugel, 1983).

4.3 Results

4.3.1 Prediction of bark thickness

To subtract the bark from the wood volume, models for the double bark thickness over branch diameter are necessary. The predicted double bark thickness enabled the bark subtraction from both sides of the RBS diameter measurements. The commonly used double bark thickness model of Altherr et al. (1978) was parameterized with stem and branch disks of diameters above 7 cm. As the wood volume model in this study should be able to predict smaller branches as well, parameterization of an own bark thickness model became necessary. In addition, comparison of the observed bark thickness to the predicted bark thickness with the equation by Altherr et al. (1978) revealed that application of the Altherr model would have led to an overestimation of the bark thickness. The estimated double bark thickness with the function by Altherr et al. (1978) was 1.4 mm higher than with the new parameterized function for branches with a diameter of 10 cm. For branches with diameter of 30 cm, the difference amounted to 3.1 mm.

The double bark thickness regression equation was calculated via a *Generalized Additive Mixed Model* (Wood, 2006) using the untransformed normally distributed identity link function. A linear curve trend was found in the bark thickness model (Fig 4.3). There were multiple measurements in one tree (see section 4.2.2). To exclude regional as well as tree specific influences, the tree id was considered a random effect. As we found heteroscedasticity, we weighted our data by a power function, which was parameterized by the model residuals over the fitted values.

The model (Table 4.3) represented a valid method for subtracting bark from both sides of every morphological RBS diameter measurement. The volume calculation after bark subtraction via RBS thus predicts the volume under bark. This was also done for the section-wise stem diameter measurements to predict the stem wood volume under bark.

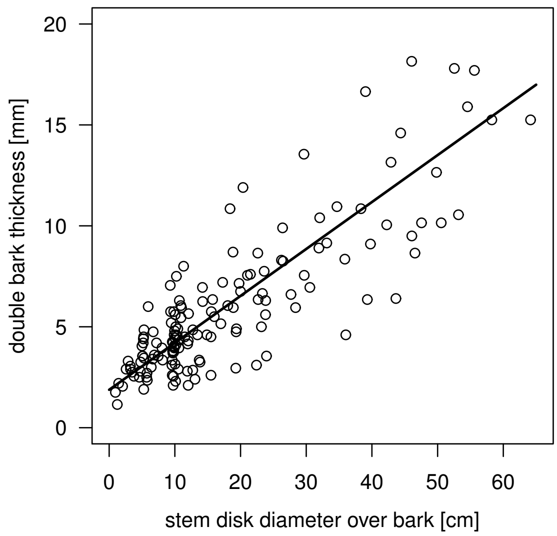

Figure 4.3: Double bark thickness over disk diameter (over bark) and the fitted linear bark thickness model.

Table 4.4: Summary statistics of all used variables, c. v. = coefficient of variation.

variable		unit	min	median	mean	max	c. v.
diameter at breast height	DBH	[cm]	8.0	34.8	35.4	78.3	-
tree height	H	[m]	13.1	26.0	25.3	38.5	-
whole tree wood volume	V_t	[m^3]	0.05	1.46	2.25	11.70	0.07
crown wood volume	$\hat{V}_i(0)$	[m^3]	0.01	0.64	1.21	9.20	0.22
tree wood volume (u. b.)	V_{tub}	[m^3]	0.04	1.36	2.11	10.98	0.07
crown wood volume (u. b.)	V_{cub}	[m^3]	0.01	0.59	1.12	8.62	0.22
median branch diameter	$F(d_{0.5})$	[m^3]	23	138	152	406	-
height at crown base	CB	[m]	1.6	10.9	10.8	21.1	-
diameter ratio at crown base	DR	-	0.2	0.4	0.4	0.9	-

4.3.2 Economically viable wood volume in the crown

Crown type differentiation

All calculated and measured crown morphology variables and tree metadata, including mean coefficient of variation for the data estimated by the RBS method, are summarized in Table 4.4. The crown type classification analyses were based on the median branch diameter and the branch diameter quartiles. The other tree variables were then used to parameterize a prediction model for the crown type classes.

The trees were clustered into 3 groups, where 50 trees were assigned to the first (bulk of volume in smaller branches), 69 to the second (balanced volume allocation) and 44 to the third (bulk of volume in larger branches) crown type. As median and quantile tree diameters cannot be measured practically but the model shall be applicable in forest management, the influence of measurable variables on the crown types was assessed. The influence of tree attributes on the crown type was tested by linear discriminant analysis (Venables & Ripley, 2002), analysis of variance and deviance (Chambers & Hastie, 1992) as well as analysis of Akaike Information Criterion (Akaike, 1981). Only significant variables and interactions were chosen as regression parameters (Table 5). The

Table 4.5: Summary statistics of the multi-nominal logistic crown type prediction model with independent variables DBH [cm], tree height (H) [m], height at crown base (CB) [m] and branch diameter ratio at crown base (DR) including the results of the leave-one-out cross-validation (c.-v.) and the within-model reclassification (w.-m.).

	crown type 2		crown type 3	
variable	coefficient	standard error	coefficient	standard error
intercept	10.3679421	0.005	20.39087	0.011
DBH	-0.4522104	0.105	-0.8534910	0.164
H	-0.2423880	0.096	-0.3248841	0.130
CB	-0.1208192	0.083	-0.2971321	0.108
DR	-20.1534122	0.006	-31.3965027	0.005
DBH*H	0.0156519	0.003	0.0244615	0.004
DBH*DR	0.7159227	0.179	0.5762532	0.368
H*DR	0.6833604	0.143	1.0091659	0.242
DBH*H*DR	-0.0266986	0.005	-0.0218313	0.007
number of observations				163
AIC				312.0
residual deviance				276.9
proportion of correct classified crown types (c.-v.)				0.50
proportion of correct classified crown types (w.-m.)				0.56

Table 4.6: Proportion of economically viable crown wood in beech crowns according to the whole crown wood (each under bark). n. d. = no data.

	DBH-interval [cm]							
crown type	[0-10)	[10-20)	[20-30)	[30-40)	[40-50)	[50-60)	[60-70)	[70-80)
1	n .d.	0.19	0.35	0.57	0.71	0.74	0.84	0.80
2	0.00	0.25	0.42	0.65	0.72	0.71	0.84	0.80
3	0.08	0.27	0.57	0.77	0.88	0.86	0.89	n. d.

analysis of variance revealed the significance of the diameter ratio at crown base DR. Deviance of the residuals (310.3 without DR) as well as AIC (330.0 without DR) were also substantially improved by this variable. Due to their high linear correlation with the significant variables, tree age and crown width were insignificant. The model is applied by plugging the coefficients of Table 4.5 into Equation 4.4.

Modelling the economically viable wood volume in the crown

Table 4.6 shows that crown type 3 crowns yielded more economically viable wood volume than the other two types for trees with similar DBH. The percentage volume of economically viable wood modeled in relation to the whole wood volume from the crown was considerably different among the crown types. Especially crowns of type 3 differed from the other 2 types. The small-end diameter of the trees did not differ between the diameter-crown type-groups from Table 6. In all DBH-crown type-groups, except for the groups below 20 cm, the group mean of the small-end diameter was randomly scattering around 10 cm. Trees in the groups below 20 cm DBH usually don't show crown branches with a base diameter of 10 cm. Their group mean small-end diameter was not calculated.

The model output data revealed that the return per m^3 substantially differs between the crown types (Figure 4.4). Trees with crowns of the type 3 showed in mean highest returns per m^3 while crowns of the type 1 were by trend lowest marginal returns over the entire observed diameter range.

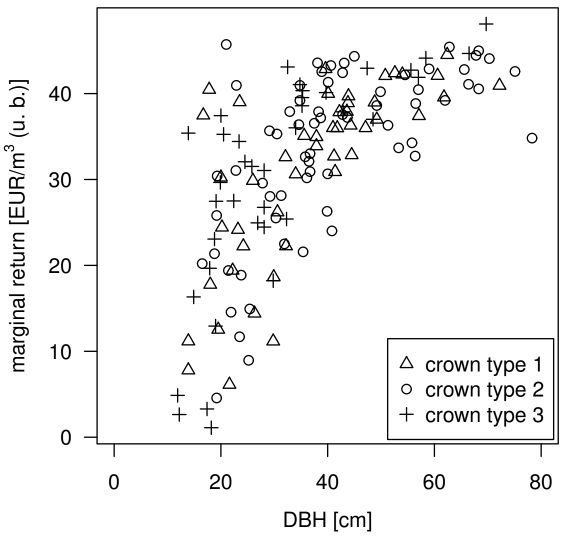

Figure 4.4: Marginal return divided by volume (under bark) versus DBH differentiated by crown types.

For sensitivity analysis of the model, the arithmetic mean of the economically viable wood volume from the crown (under bark) was calculated with all 163 trees (Figure 4.5, left). The reference was the common scenario (revenue: 50 € m^{-3}, costs: 0.35 € processing $step^{-1}$). Changes in costs as well as changes in revenues of 20 % led to a change of the mean predicted crown wood volume up to 5 %. Decreasing of revenues and costs affected the economically viable crown wood volume slightly more than respective increasing. The small-end diameter (at which cutting was stopped) was influenced by changing costs and revenues as well (Figure 4.5, right). With values ranging from 5 to 16 cm, the median small-end diameter of the common scenario was ca. 10 cm. 20 % increasing costs increased the small-end diameter to a median of 11 cm with values ranging from 6 to 16 cm. 20 % decreasing costs led to small-end diameters ranging from 5 to 15 cm with median 9 cm. By 20 % increasing revenues decreased the median of the small-end diameters to 9 cm. Respective increasing of the costs led to a median small-end diameter of 11 cm. While differing costs as well as differing revenues led to a substantial change of the median small-end diameters, the distributions of the small-end diameters around the median were always approximately unchanged. The distribution of each scenario was symmetric with 1.5 quantiles ranging ca. 6 cm around the median. It additionally became obvious that simultaneous changing of costs and revenues did not change the median small-end diameter as well as the distribution around the median (Figure 4.5, right). The economically viable wood volume as well as the median small-end diameter thus only changed when one of the input variable changes while the respective other stays constant or changes in the opposite direction.

The economically viable crown wood volume of European beech [m^3] (under bark) V_v, modeled with the introduced algorithm, was fitted to the exponential growth function (see Equation 4.5). The regression depended only on the covariate DBH d [cm] and the crown type, which functions as dummy variable ct_i. Following Equation 4.5, the growth function can be written as

$$V_v = exp\left(log\left(\beta\right) + d_{ct1}\gamma_{ct1} + d_{ct3}\gamma_{ct3}\right)\mathrm{DBH}^{\alpha} \tag{4.6}$$

The parameters values are shown in Table 4.7. d_{ct1} and d_{ct2} are dummy-variables. They are 1, if the volume of the respective crown type is to be predicted. If the volume of crown type 2 is

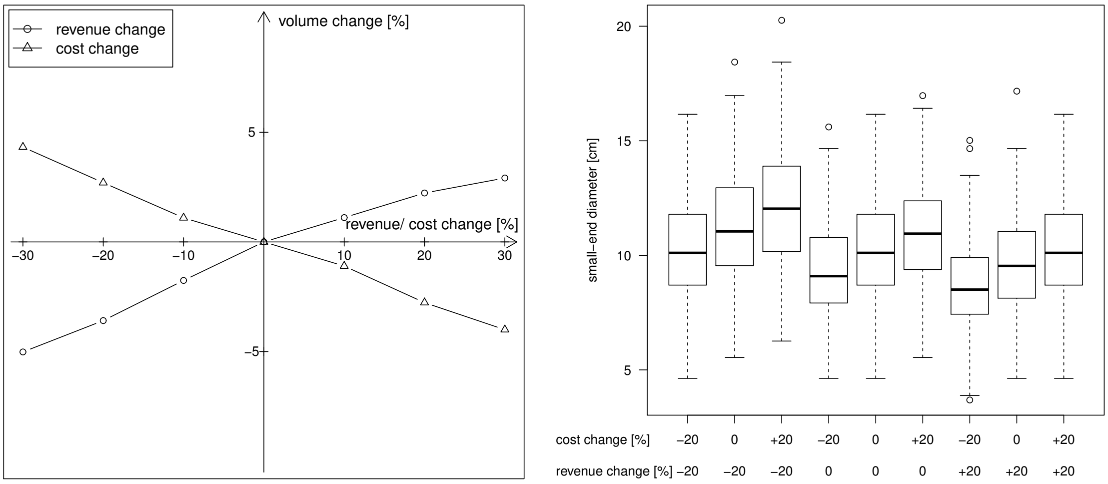

Figure 4.5: Relative change in the predicted economically viable crown timber volume over relative changes in costs and revenues (left) and the distribution of the small-end diameters at cost and revenue changes of 20 % (right).

Table 4.7: Summary of the economically viable crown wood volume regression model. The data was fitted to a natural exponential function by the generalized nonlinear regression method with the independent variables DBH and the crown type.

variable	coefficient	standard error	t-value
$\log(\beta)$	-13.30117	0.114	-116.57
γ_1	-0.06699	0.031	-2.19
γ_3	0.19360	0.034	5.73
α	3.48463	0.031	112.7
number of observations		1347	
deviance explained		0.89	
model range [cm]		0-78	
AIC		-1022.9	

to be predicted, both dummy variables must be set to 0. All further continuous covariates did not lead to a significant model improvement. Cost as well as revenue changes of 20 % were partially significant. However, the dimension of these variables in comparison to the crown type dummy variables were low and the improvement of the AIC (-1027.3) was thus only very slight. Altogether, the slight model improvement does not justify consideration of the abstract and non-measurable cost and revenue change dummy variables. They were not chosen as model parameters. The same was found for cost and revenue changes up to 30 %.

The difference between economically viable wood volume of crown type 1 and 2 was comparatively low (Table 4.7), whereas the difference between crown type 2 and 3 was approximately 20 %.

4.3.3 Allometric relationships

The whole tree and crown wood volume both revealed an allometric relationship to DBH (Figure 4.6a and b). Both relationships showed heteroscedasticity in the untransformed, and homoscedasti-

Table 4.8: Summary of the log linear regression models, fitted by the SMA method. α and $\log(\beta)$ are the model coefficients; l.ci.lim is the lower, u.ci.lim the upper limit of the 95 % confidence interval; r^2 is the linear coefficient of determination.

allometry	α	l.ci.lim	u.ci.lim	$\log(\beta)$	r^2
$V_f \propto DBH^\alpha$	2.492	2.444	2.541	-8.408	0.98
$V_c \propto DBH^\alpha$	2.915	2.812	3.022	-10.661	0.95
$V_c \propto V_f^\alpha$	1.170	1.131	1.209	-0.821	0.95
$H \propto DBH^\alpha$	0.490	0.448	0.536	1.519	0.67
$MB \propto DBH^\alpha$	1.179	1.091	1.275	0.842	0.74

city on the double log transformed scale. The coefficients of determination of the relationships were very high, whereby the coefficient of determination of the crown wood volume-DBH relationship was slightly lower. There were no differences between the clustered crown types. The whole crown volume did not depend on the crown type (Table 4.7).

Crown wood volume was found to increase disproportionally high with whole aboveground wood volume (c). Further, relationships like tree height-DBH and median branch diameter-DBH (d) showed a lower coefficient of determination and thus a higher variance than the former relationships (Figure 4.6a, b and c).

4.4 Discussion

4.4.1 Estimation of bark thickness

The most commonly used linear bark thickness function by Altherr et al. (1978) is only valid for branches with diameter > 7 cm. Since our viable wood volume should be able to predict smaller branches as well, the function by Altherr et al. was not applicable for our purposes. Furthermore, biomass thickness is known to have regional differences (Bonyad et al., 2012). As Alterr et al. collected their data in the southwest of Germany only, application of their model could lead to wrong predictions. Actually the function by Altherr et al. would have let to an overestimation of our measured bark thicknesses. Application of our new parametrized bark thickness model in further studies appears to be useful whenever regionalized functions are not available or when bark thicknesses of smaller branches (diameter < 7 cm) have to be predicted.

4.4.2 Economically viable wood volume in the crown

The mains advantage of the RBS method are its unbiasedness, its efficiency and its flexibility. Based on the morphologic measurements, it is possible to estimate the volume of various parts of the crown. In our approach, we focused on the economically viable branch structures. Although the measurements for this study were relatively time and cost expensive they represent an efficient trade-off between accuracy and measuring costs.

Crown type differentiation

The different types of volume distributions according to the branch diameters in the crowns $F(d)$ (Figure 4.2) indicate that different harvesting volumes in the tree crowns can be caused by the wood allocation. It is, from a practical perspective, immediately apparent that crowns with more wood volume in relatively large branch dimensions lead to higher yields than crowns with a lot of wood volume in relatively small branch dimensions. Branches with larger dimensions lead to

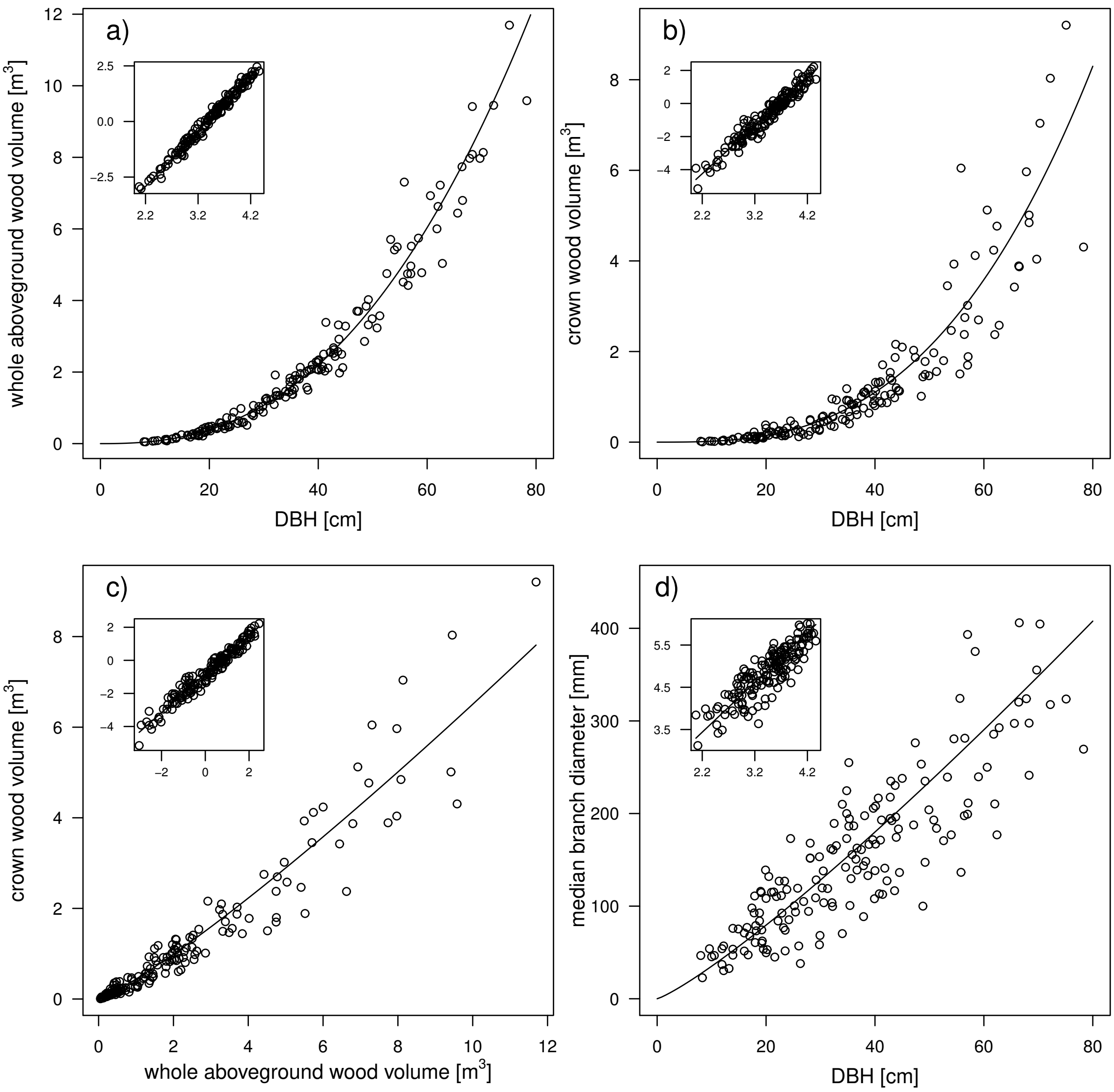

Figure 4.6: Allometric relationships of the whole aboveground wood volume (a), the crown wood volume (b) and the median branch diameter (d) over DBH as well as crown wood volume over total aboveground timber volume (c) incl. the back transformed regression function. The small windows show the logarithmic transformed data and the log linear regression function.

lower procession costs per cubic meter (Neumann-Spallart, 1952). While the variability in the cumulative volume is high, the general curve tends to be uniform over all trees (Figure 4.2).

To create a variable which is able to describe this economically relevant branch dimension numerically, the median and quantile diameter were calculated from the volume distribution of the branch diameter $F(d)$. Since a major part of the wood volume in type 1 crowns is allocated to relatively small branches and twigs, this crown type is the economically unfavorable in comparison to the other types. Classification of crown type appears to be a great advantage in forest planning as it enables a more accurate evaluation of the expectable wood amount from the crown of a tree.

The median and the quartiles of branch diameters are suitable for crown type classification but, unfortunately, they are not practically measurable. For this purpose, after the classification via median and quantile branch diameters, further relationships between tree parameters and the crown types were examined. The prediction model (Table 4.5) enables a crown type classification as part of the forest inventory. When applying the crown type prediction model, there is no need to measure the branch diameter ratio at crown base. A visual suggestion of the ratio in discrete steps of 0.1 from 0.2 to 0.9 is adequate. Plugging in the actual measured diameter ratio and the discrete diameter ratio that was rounded to 1 digit leads to the same crown type classification.

Modelling the economically viable wood volume in the crown

The model (Algorithm 4.1) provides an approach for separating the economically viable wood volume from the whole wood volume in the crown. The advantage of the model lies in the type of data that is used in its parameterization. Instead of taper functions, the model bases on the actual morphological form of the crown. The economically viable wood volume model does not consider external factors like log quality or processing restrictions (e.g. fixed log lengths or minimum/ maximum log diameters). Therefore, the predicted wood volume represents the maximum economically viable wood volume of a European beech tree crown. More, or less processed wood volume would lead to a lower marginal return.

For model simplification, we assumed the marginal processing costs of per piece to be equal. They were interpreted as fixed costs per processed branch structure. In practice, however, processing costs also depend on variable factors like branch diameter and branch length. As reliable time studies for this specific working progress are lacking, average costs were derived from the wages tables of the forest entrepreneur association. The model basically combines the RBS estimation method with a break-even analysis. Further costs, which not directly affect the procession of the crown were thus not relevant for the break-even analysis (Starr & Tapiero, 1975; Varian, 2010). Costs for felling and logging, for instance, were thus not implemented.

The absolute marginal return increases with DBH. Since the marginal return depends on costs and revenues, the variance in marginal return over DBH is influenced by tree wood volume distribution (which is directly linked to the revenue) and branching intensity (which is directly linked to the costs). It is thus evident, that type 3 crowns result in lower costs at constant volume, or significantly more volume at constant costs and, finally, in a higher marginal return, respectively (Figure 4.4, Table 4.7).

Figure 4.5 (right) reveals one of the main advantages of our model. It can be seen that there is no general threshold diameter where processing ends but tree specific small-end diameters. Over all scenarios of the sensitivity analysis, these small-end diameters range from ca. 5 to ca. 17 cm. It becomes obvious that the median small-end diameter changes with differing costs or revenues but the distribution around the median does not. This means that changes in revenue or costs affect each small-end diameter in approximately the same amount. Extreme small-end diameters thus react similar to changes as small-end diameters near the median. The fact that simultaneously changing costs and revenues do neither change the median nor the distribution of the small-end diameters (Figure 4.5, right) was expectable. The economically viable wood volume model in principle compares the revenues of one wood structure with its processing costs. As simultaneous changes of both variables do not change the result of the comparison (Algorithm 4.1), the output of the model is unchanged. With view to a future application of our model, this is advantageous. The model output will be valid in future as long as costs and revenues develop in similar amount.

The small-end diameters do not differ between the crown types. This is not surprising since the break-even point (Algorithm 4.1) is determined by piece-volume of the last branch structure (the last viable branch structure). This piece volume is similar in all 3 crown types. The economically viable wood volume is nevertheless different between the crown types since the volume distribution up to this last economically viable branch structure (Figure 4.2) is substantially different. The viable wood volume is thus less dependent on the small-end diameter than on the wood volume distribution up to this diameter.

The regression analyses translated the output of the economically viable crown wood model into an applicable regression model (Table 4.7). Only DBH and crown type were significant. This is not surprising as the information of morphological variables are encompassed in the crown type dummy variable. The significant crown type dummy represents the difference in crown type 1 or 3 to crown type 2. Due to insufficient number of observations the interaction between crown types dummy and β cannot be clarified ultimately. Since residual analyses did not reveal systematic errors, the model validity was not compromised.

Changes in processing costs as well as changes in revenue changes in the timber price had by far less explanatory content than the crown morphology dummy variable. The economically viable wood from beech crowns changes, even for a small increase of harvesting costs, but the change may be small. Consideration of the crown type was therefore much more important for models accuracy than consideration of the costs and revenue changes. The viable wood volume from complex crowns of European beech is thus driven by the morphological variable. The absence of the cost and revenue parameter was not surprising since it was shown that simultaneous development of costs and revenue do not affect the small-end diameter (Figure 4.5, right). It became clear that development of costs and revenues up to 20 % would not lead to remarkably different harvesting volumes. Only if either the processing costs or the timber price changes > 30 % whereat the other variable does not change, the introduced regression model would lead to wrong predictions of the economically viable wood volume.

4.4.3 Allometric relationships

Since all relationships showed a log linear trend and an homogeneous variance (Figure 4.6), all assumptions for allometric regressions were met (Stumpf and Porter, 2012). The strong relationship between the crown wood volume and the DBH as well as between the crown wood volume and the tree wood volume (Table 4.8) was expectable, as this was already observed in further studies (e.g. Niklas, 1994; Pretzsch & Dieler, 2012). However, it must be considered that all our sample plots were high forests under standard regimes, their intra- and interspecific competition were thus similar. The influence of the competition on the allometric relationships, as it was observed by Pretzsch & Dieler (2012), can neither be confirmed or declined with the data of this study.

The coefficients of determination of the log linear models between two variables (Table 4.8) were interpreted as the expression of their natural variability. Variables with high coefficients of determination have a very close relationship and show slight natural variation. The whole above-ground wood volume as well as the crown wood volume relationships over DBH were strongest. It is therefore evident that neither of those two variables was influenced notably by other variables than the DBH. Because of these strong relations between the whole aboveground wood volume as well as the wood volume from the crown to the DBH, different harvesting volumes from beech trees with similar DBH, as they can be observed in forest practice, cannot be caused by different absolute wood volumes of those trees. Differences in the harvesting volumes must be driven by other factors affecting the amount of harvestable wood from beech crowns.

Relationships like the median branch diameter over DBH showed substantially lower coefficients of variation. As the median branch diameter is an auxiliary variable for the morphological appearance of the crown, it is evident that the morphological form of the crown is comparatively volatile over DBH. The median branch diameter affects the economically viable wood volume significantly (Table 4.7). The relationship of the economically viable wood volume in the crown over DBH is thus not as strong as the relationship between the whole wood in the crown. It is, to conclude, not the absolute wood volume in the crown but the viability of this wood volume, which is driven by morphological patterns, that explains different harvesting wood volumes for European beech trees with similar DBH. Volume models, able to differentiate between the whole and the actually viable wood volume, are thus of high practical importance.

4.5 Conclusions and outlook

Analysis of the allometric relationships shows that the proportion of wood from the crown, in relation to wood from the stem, grows with increasing DBH (Figure 4.6). It is therefore essential to consider the predicted wood volume from the crown as a by-product of stem wood production in the operational planning. It was shown that prediction of the whole wood volume from the crown of European beech trees is relatively simple (Table 4.8, $r^2 = 0.95$) and that additional information is needed to differentiate the economically viable wood from the whole wood volume in the crown (Table 4.7, pseudo-$r^2 = 0.89$).

One of the main functions of the crown is to optimize the position of the leaves in relation to light radiation (Mitscherlich, 1970). Crown appearance depends on various influences, like atmospheric conditions (Gruber et al., 2004), competition (Umeki, 1995; Pretzsch & Dieler, 2012) and genetically-determined apical control (Wilson, 2000). This leads to a high morphological variability in crown appearance (Roloff, 1986; Schröter et al., 2012). While the whole wood volume in the crown can be predicted via DBH (Pretzsch & Dieler, 2012), the economically viable wood volume is highly dependent on the crown morphology. Because of this strong relationship between DBH and crown wood volume (Table 4.8, $r^2 = 0.95$), prediction of branch volume or biomass from the crown via existing function (see e.g. Zianis et al. (2005) for a broad overview of existing functions) is certainly valid and effective. Most of the recent literature functions, however, provide prediction of the wood volume or biomass up to certain small-end branch diameters (often 7 cm). The choice of those diameters appears to lack economically interpretation. We observed that every tree had a specific individual small-end diameter (Figure 4.5, right). Our approach thus appears to be advantageous over classical functions as it is not driven by a specific, not interpretable diameter but by the measured and economically rated actual branch structure of the crown. It thus enables, in contrast to classical approaches, a sophisticated prediction of the effectively expectable wood volume from the crown. It was further shown that the tree specific, economically justified small-end diameters do not further change with differing processing costs or revenues. Every tree has a specific small-end diameter where reasonable processing ends. This specific small-end diameter is relatively robust against cost and revenue changes.

Our morphological approach for modelling the economically viable wood volume of deciduous tree crowns has to be classified as a scientific *deductive-nomological* model (Hempel & Oppenheim, 1948) that is able to describe the causal connection between crown morphology and economic considerations theoretically. However, as we parameterized our model with realistic and recent processing costs and timber prices, the predicted viable wood volume reflects realistic dimensions. It must be kept in mind that our model underlies simplifications. Firstly, all our sample stands were silviculturally managed high forests. Secondly, further influences on the actually harvested wood volume (e.g. fixed log lengths or diameters) are not respected by our model. The modeled viable wood volume must be interpreted as the effectively expectable wood volume assuming absence of further exogenous restrictions.

The presented model assesses the optimal crown utilization intensity from an economically point of view only. As shown in Miettinen et al. (2014), tree stump and foliage usage are worthwhile when climate impacts are respected in the net benefit. Future studies could examine whether stump or foliage usage can improve the presented model and if the model is able to consider of further impacts like nutrient load damage, biodiversity benefits and climate impacts.

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Chapter 5

Flexible Global Optimization with Simulated-Annealing

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- Alexander Lange is co-author of the R package and performed the SVAR example.
- Elmar Spiegel reviewed the code of the package, supported writing of the manuscript and the review process.

Abstract

Standard numerical optimization approaches require several restriction. So do exact methods, like the Newton-Raphson or the Nelder-Mead approach appeal for linearity and unimodality of the loss function. One method to relax these assumptions is the Simulated Annealing approach. There the risk of ending in a local optima is reduced. However the standard implementation still need regular parameter spaces and continuous loss functions. Therefore we implemented a version of the Simulated Annealing method that is able to deal with irregular and complex parameter spaces as well as with non-continuous and sophisticated loss functions. Moreover to gain fast but still reliable solution we included steps to shrink the parameter space during the iterations. All these steps are summarized in the R-package **optimization**, which we will introduce in the following article. Therefore we also included generic and real world applications of our approach.

5.1 Introduction

As early computer-based optimization methods developed contemporaneously with the first digital computers (Corana et al., 1987), nowadays numerous optimization methods for various purposes are available (Wegener, 2005). One of the main challenges in Operations Research is therefore to match the optimization problem with a reasonable method. The complexity of the problem thereby qualifies the possible methods. Optimization procedures in general can be distinguished into exact methods and heuristics (Kirkpatrick et al., 1983). For simple optimization problems, exact methods are often meaningful tools of choice. If all assumptions on model loss and restrictions are met, these methods will obligatorily find the exact solution without need for further parameters. They are the easiest way of solving optimization problems. The *Linear Simplex-Method* (Dantzig et al., 1959) as an example which only needs the loss-function and optional restrictions as model input. If, however, any of the model assumptions, e.g. linearity or unimodality, is violated, exact methods are unable to solve problems validly. With developing computer power, heuristics like the *Savings-Algorithm* (Clarke & Wright, 1964) and metaheuristics like *Simulated Annealing* (SA) (Kirkpatrick et al., 1983) became popular. They enable solving more complex optimization problems. Metaheuristics are a generalization of heuristics with aim to be even more flexible and efficient (Blum & Roli, 2003) such that they can solve complex optimization problems, like nonlinear problems. Direct search methods like the *Nelder-Mead* (NM) algorithm are comparatively efficient methods which directly converge to the functions optimum and need relatively less settings (Geiger & Kanzow, 1999). Random search methods are able to cope with multimodal objective functions. Depending on the method of choice, more or less assumptions on the loss function can be neglected on the one hand. On the other hand, heuristics and metaheuristics will always solve problems approximately. Precision of the solution depends on the optimization method and further parameters. There is even no guaranty of approximating the actual optimum since the solution also depends, by contrast to exact methods, on parameterization (Blum & Roli, 2003). Definition of proper parameters is thus a crucial point of those methods. The complexity of parameterization will by trend increase with flexibility of the method while efficiency trends to decrease. The efficiency and accuracy of such models is strongly sensitive to their parameter specification (Corana et al., 1987). Heuristics are often programmed for multi-purpose usage such that there is a suitable method for many optimization problems. For complex optimization problems, however, multi-purpose optimizers often fail to find solutions. Furthermore multi-purpose optimizers are usually not suitable or not efficient for highly complex problems like problems with restricted parameter space. Whenever general-purpose optimizers are too restrictive or inflexible to solve a problem properly, specific methods are advantageous. Those offer a lot of variable parameters such that they be parameterized very specific to the optimization problem. They represent the most flexible and the most complex optimization methods (Blum & Roli, 2003).

SA (Kirkpatrick et al., 1983) is known to be one of the oldest and most flexible metaheuristic method, though the term metaheuristic was established after initial publication of SA (Blum & Roli, 2003). It is known to be favorable against many other methods for multimodal loss functions with a very high number of covariates (Corana et al., 1987). The method was applied in many studies among several fields covering e.g. chemistry (Agostini et al., 2006), econometrics (Ingber, 1993) or forest sciences (Baskent & Jordan, 2002; Boston & Bettinger, 1999). Since its first implementation by Kirkpatrick et al. (1983), many authors have modified the algorithm in order to adopt it for specific problems (e.g. DeSarbo et al., 1989; Goffe et al., 1996) or make it more general (e.g. Xiang et al., 2013). It basically combines systematic and a stochastic components, thus enables escaping local optima. It is hence typically used for global optimization of multimodal functions. As it offers a lot of options, SA can be named as hybrid method between a general optimizer (when default values are chosen) and a problem specific optimization algorithm (Wegener, 2005). Corana et al. (1987) developed a dynamic adoption method for the variation of the stochastic component during the optimization process. Their modification affects the efficiency as well as the accuracy of the SA algorithm. It has potential to substantially improve the method. Pronzato et al. (1984) suggest to decrease the search-domain of the stochastic component with increasing number of iterations. The stochastic component in general is the most sensitive part of the method since it actually determines the loss variables modification during the iterations.

The R software environment provides platform for simple and effective distribution of statistical models to a huge user community (Xiang et al., 2013). Thus, not surprisingly, several optimization packages of high quality can currently be purchased via *Comprehensive R Archive Network* (Theussl & Borchers, 2016) where even the SA method is recently listed five times. We, however, believe, there is need for a specific stochastic optimization package for complex optimization problems. A package coping with very flexible user definable loss functions with multiple options could be an advantageous extension for R. There is demand for specifically definable optimization problems. We therefore present the package **optimization** which is basically a modified version of SA. We used the properties of SA to program a stochastic optimization method for specific purposes. We therefore focused on flexibility and implemented many user specifiable parameters. Our method is, in its default configuration, usually not immediately efficient on the one but flexibly adoptable to specific purposes on the other hand. Main advantages of the package are the possibilities to specifically adjust covariate changing rules as well as the the robustness of the loss function. The changing rule allows the user e.g. to define an integer parameter space. The loss function can return any value, even `NA` or `NaN` are possible. Several further user specifications help to parameterize the model problem-specific such that the user can influence accuracy and speed very detailed. It is moreover the first R function where the improvements of Corana et al. (1987) and Pronzato et al. (1984) are implemented into an SA based optimization software. This means, the search domain of the stochastic component of SA dynamically shrinks with increasing iterations. We also implemented a generic plot function for post-hoc inspection of the model convergence assessment and the solution quality. In the following, we briefly introduce the algorithm methodologically and explain the most relevant parameters. We show in four examples where our model is favorable against existing methods and explain how it can be parameterized. We develop two examples illustrating the basic model behavior with focus on the covariate changing rule. Moreover we give hints how to adopt the numerous options to specific problems. Two practical examples where our function is recently used underpin the relevance of our specific-purpose optimization method. One of them, the optimization of forest harvesting schedules is a relatively complex example which cannot be solved with any other optimization function in the R framework.

5.2 The package optimization

In this section, theory of our SA interpretation and resulting parameters are explained.

5.2.1 Method

Since the basic idea of classic SA is derived from the physical process of metal annealing, the nomenclature of SA comes particularly from metallurgy. Just as the classic SA, our function is composed of an inner for and an outer while loop (Kirkpatrick et al., 1983). The number of iterations in both loops can be defined by the user. For better overview, we displayed the important steps of our function in a pseudocode (Algorithm 5.1).

Inner loop

Function of the inner for loop (Algorithm 5.1, lines 4 to 29) is basically to draw covariate combinations stochastically and to compare the returns. The loop repeats n_{inner} times. First operation of the inner loop (line 5) is saving the covariate combinations of the last inner iteration as x_j. In the first iteration x_j is the vector with user defined initial covariates.

Secondly (line 6), the covariates are changed. This changing process is an essential difference between our approach and the other SA based method in the R framework. Shape and behavior of the variation process may be defined by the user and may be dynamic. Hints and examples for specifying this variation, which is a user defined R function, will be given in the following sections. The variation function *vf* is used to create a temporary vector of covariates x_{i*}. Besides the former covariate combination x_j, the variation function is allowed to depend on a vector with random factors *rf* and the temperature *t*. Since *rf* and *t* change over time, the variation function thus can have dynamic components. Adjustment of *rf* and *t* is done in the outer loop which will be explained explicitly in the following subsection. In the classical SA approach, the covariates x_{i*} are generated by adding or subtracting a uniform distributed random number to x_j (Kirkpatrick et al., 1983). The range of the uniform random number is, in our function, determined by *rf* whereas *rf* is relative to x_j. A random factor of 0.1 and a covariate expression of three e.g. leads to a uniform random number between 2.7 and 3.3. This standard variation function is also default in our approach. A very simple exemplary modification of the variation function could e.g. be a normally distributed random number with mean x_j and standard deviation *rf*.

After generating x_{i*}, the boundaries are checked (lines 7 to 15). If all entries in x_{i*} are within their respective boundaries, the response is calculated. Otherwise the invalid entries of x_{i*} are drawn again until all entries are valid. According to Corana et al. (1987), the number of invalid trials can be a useful information to assess quality of the search domain. The numbers of invalid trials are thus counted and stored (line 13) in order to make this information accessible for the outer loop. Counting of valid as well as invalid trials is not reseted after each inner loop repetition. Both are only initialized in iteration one of the inner loop and increase till the last iteration.

Next step is the comparison of loss function returns (lines 16 and 17). If the return of current variables combination $f(x_{i*})$ is better than $f(x_j)$, x_{i*} and $f(x_{i*})$ are stored into x_i and $f(x_i)$, so x_i are the initial covariates for the next iteration. Core idea of the classical SA approach is to cope with local optima. Thus, even if $f(x_{i*})$ is worse than $f(x_j)$, there is a chance of storing x_{i*} into x_i (lines 18 to 25). The likelihood of keeping worse responses depends on the Metropolis probability M (Metropolis et al., 1953).

$$M = exp\left(-\frac{\mid f(i_*) - f(j) \mid}{kt}\right), \tag{5.1}$$

with k being a user definable constant. We adopted this strategy from classic SA without modifications. M decreases with decreasing temperature t. The likelihood of keeping worse responses

1 initialize t, vf with user specifications
2 calculate $f(x_0)$ with initial parameter vector x_0
3 **while** $t > t_{min}$ **do**
4 **for** *i in c(1:* n_{inner}*)* **do**
5 $x_j \leftarrow x_{(i-1)}$
6 call the variation function to generate x_{i*} in dependence of x_j, rf and t
7 check if all entries in x_{i*} are within the boundaries
8 **if** *all* x_i *valid* **then**
9 calculate $f(x_{i*})$
10 **else**
11 **while** *any(*x_{i*} *invalid)* **do**
12 call the variation function again
13 count invalid combinations
14 **end**
15 **end**
16 **if** $f(x_{i*}) < f(x_j)$ **then**
17 $x_i \leftarrow x_{i*}; f(x_i) \leftarrow f(x_{i*})$
18 **else**
19 calculate Metropolis Probability M (Equation 5.1)
20 **if** *uniformly distributed random number [0,1]* $< M$ **then**
21 $x_i \leftarrow x_{i*}; f(x_i) \leftarrow f(x_{i*})$
22 **else**
23 $x_i \leftarrow x_j; f(x_i) \leftarrow f(x_j)$
24 **end**
25 **end**
26 **if** *threshold accepting criterion fulfilled* **then**
27 break inner loop
28 **end**
29 **end**
30 reduce t for the next iteration
31 rf adaptation for the next iteration
32 **end**
33 **return** optimized parameter vector, function value and some additional information

Algorithm 5.1: Pseudocode of the `optim_sa` function in the **optimization** package exemplary for a minimization.

thus decreases with decreasing temperature t (lines 19 and 24). t does not change during the entire inner `for` loop. The likelihood of keeping worse values is thus equal for each response until the inner loop is finished. Modification of t is part of the outer loop which will be explained in the next paragraph. In case a worse result is chosen the former optimal covariate combination is, of course, stored before it is overwritten since otherwise there is a sound chance of overwriting that actual global optimum. More details of the Metropolis probability can i.a. be found in Kirkpatrick et al. (1983) and Metropolis et al. (1953).

Storing information on development of covariates and response can help improving the performance of SA (Lin et al., 1995; Hansen, 2012). We implemented a threshold accepting strategy (Dueck & Scheuer, 1990) into our SA interpretation (lines 26 to 28). This criterion is the only module that allows reducing the inner loop repetitions without direct user influence. It is simply a vector where the absolute differences of $f(x_i)$ and $f(x_j)$ are stored. If the response oscillates for user defined number of repetitions within a user defined threshold, the inner loop breaks.

Outer loop

Main functions of the outer while loop (lines 3 to 32) are calling the inner loop (lines 3 to 29) and modifying the parameters that are needed in the inner loop (lines 30 and 31). Therefore t and rf only change after completely finishing an inner loop. The outer loop repeats till t is smaller than the user defined minimum temperature t_0.

After finishing the inner loop, firstly t is adjusted (line 30). t is necessary for the stochastic part in the inner loop (line 19, Equation 5.1). In our function, t is obligatory decreasing as it is calculated by multiplying the temperature of the current iteration by r which is a user defined real number between 0 and 1. The number of outer loops repetitions is thus implied by initial temperature t_0, t_{min} and r.

Afterwards rf changes (line 31). The dynamic adaption of rf after Corana et al. (1987) and Pronzato et al. (1984) is another major novelty of our function. As each covariate can have its own random factor, rf is a vector of the same size as x_i. rf is needed for the covariate variation in the inner loop (lines 6 and 12). Dividing the numbers of invalid trials which were counted in the inner loop (line 13) distinctively for each covariate by the total number of trials of the respective covariate gives the ratio of invalid trials for each covariate. According to (Corana et al., 1987), this ratio of invalid trials can be used to find a trade-off between accuracy on the one and size of the search domain on the other side. They argument that if only valid covariate combinations are drawn, the search domain could be too small for multimodal problems. For this, the ratio of invalid trials in the current iteration is used to generate the rf for the following outer loop repetition. They suggest ratios between 0.4 and 0.6. If any observed ratio of invalid trials is < 0.4 or > 0.6, the respective random factors are modified following the suggested equation by Corana et al. (1987). This strategy allows a adjustment of rf for the next iteration. Pronzato et al. (1984), who developed the *Adaptive Random Search method*, propose a time decreasing search domain. Thus they suggest a search domain adjustment that does not depend on former information, as Corana et al. (1987) did, but on the number of iterations. They argument that the search domain should be wide at the beginning to give the algorithm the chance of coping local optima and small in the end to allow higher precisions since the algorithm should converge to the global optimum at the end. Later iteration thus need smaller search domains than earlier iterations. We combined the idea of Pronzato et al. (1984) into the dynamically search domain adjustment of (Corana et al., 1987) by linearly shrinking the favorable range of ratios from the suggested ratios (0.4-0.6) to 0.04-0.06. As mentioned in the inner loop explanations, the variation function can be user defined (lines 6 and 12). The user thus has the chance of defining flexibly in which way t and rf influence the covariate variation. Per default, the search domain around the covariates shrinks by trend with increasing number of outer loop iterations.

5.2.2 The function optim_sa

`optim_sa` shall be able to solve very specific optimization problems, several parameters can be defined by the user. Quality of solution and speed of convergence will thus substantially depend on accurate parametrization. In the following, we will explain the most important parameters briefly giving hints for useful specification. A complete parameter list can be found in the vignette.

- `fun`: Obligatory loss function to be optimized. The function must depend on a vector of covariates and return one numeric value. There are no assumptions on covariates and return. The covariates not even need to be continuous. Missing (`NA`) or undefined (`NaN`) returns are allowed as well. Any restriction on the parameter space, e.g. specific invalid covariate values within the boundaries, can be integrated in the loss function directly by simply returning NA. We will be more specific on this in the practical examples.

- `start`: Obligatory numeric vector with initial covariate combination. It must be ensured that at least the initial covariate combination leads to a defined numeric response. The loss function at the initial variables combination must therefore return a defined numeric value. This might be relevant when the starting values are determined stochastically.

- `trace`: If `TRUE`, the last inner loop iteration of each outer loop iteration is stored as row in the trace matrix. This might help evaluating the solutions quality. However, storing interim results increases calculation time up to 10 %. Disabling `trace` can thus improve efficiency when the convergence of an optimization problem is known to be stable.

- `lower, upper`: Numeric vector with lower boundaries of the covariates. The boundaries are obligatory since the dynamic `rf` adjustment (Corana et al., 1987; Pronzato et al., 1984) depends on the number of invalid covariate combinations.

- `control`: A list with optional further parameters.

All parameters in the list with `control` arguments have a default value. They are pre-parameterized for loss functions of medium complexity. `control` arguments are:

- `vf`: Variation function that allows the user to restrict the parameter space. It is one of the most important differences to classic SA. The function determines the variation of covariates during the iterations. It is allowed to depend on `rf`, `temperature` and the vector of covariates of the current iteration. The variation function is a crucial element of `optim_sa` which enables flexible programming. It is (next to the loss function itself) the second possibility to define restrictions. The parameter space of the optimization program can be defined by `vf`. Per default, the covariates are changed by a continuous, uniform distributed random number. It must be considered that defining specific `rf` can increase the calculation time. The default `rf` is a compiled C++ function whereas user specified `rf` must be defined as R functions. User specified are e.g. useful for optimization problems with non-continuous parameter space.

- `rf`: Numeric vector with random factors. The random factors determine the range of the random number in the variation function `vf` relative to the dimension of the function variables. The `rf` can be stated separately for each variable. Default is a vector of ones. If `dyn_rf` is enabled, the entries in `rf` change dynamically over time.

- `dyn_rf`: Boolean variable that indicates if the `rf` shall change dynamically over time to ensure increasing precision with increasing number of iterations. `rf` determines whether the adjustments of Corana et al. (1987) and Pronzato et al. (1984) are enabled (see method section for theoretical background). `dyn_rf` ensures a relatively wide search domain at the beginning of the optimization process that shrinks over time. Disabling `dyn_rf` can be useful when `rf` with high performance are known. The development of `rf` is documented in the `trace` matrix. Evaluation of former optimizations with dynamic `rf` can thus help finding efficient and reasonable fixed `rf`. Self-specified `vf` may not depend on `rf`. In this cases activating `dyn_rf` does not change the process.

- `t0`: Initial temperature. The temperature directly influences the likelihood of accepting worse responses thus the stochastic part of the optimization. `t0` should be adopted to the loss function complexity. Higher temperatures lead to higher ability of coping with local optima on the one but also to more time-consuming function calls on the other hand.

- `t_min`: Numeric value that determines the temperature where outer loop stops. As there is practically no chance of leaving local optima in iterations with low temperature `t_min` mainly affects accuracy of the solution. Higher `t_min` yields to lower accuracy and less function calls.

- `nlimit`: Integer value which determines the maximum number of inner loops iterations. If the break criterion in the inner loop is not fulfilled, `nlimit` is the exact number of inner loops repetitions. It is therefore an important parameter for determining the number of iterations.
- `r`: Numeric value that determines the reduction of the temperature at the end of each outer loop. Slower temperature reduction leads to increasing number of function calls. It should be parameterized with respect to `nlimit`. High `nlimit` in combination with low `r` lead to many iterations with the same acceptance likelihood of worse responses. Low `nlimit` in combination with `r` near 1, by contrast, lead to continuously decreasing acceptance likelihood of worse responses. It is thus the second crucial parameter for determining the number of iterations.

5.3 Examples

To show the benefits of our **optimization** package we build four examples explaining where the `optim_sa` function can be advantageous.

5.3.1 Himmelblau Function with continuous parameter space

Himmelblau's function (Equation 5.2) (Himmelblau, 1972) was chosen as initial example since it is a very simple multimodal equation which is widely known in Operations Research. It has four equal minimum values ($min(f(x_1, x_2)) = 0)$) at {-2.8, 3.1}, {3.0, 2.0}, {3.6, -1.8} and {-3.8, -3.3} . In order to display the basic behavior of **optimization**, it was compared with two other SA methods from the packages **stats** and **GenSA**. Himmelblau's function is relatively simple. Therefore we also included the NM optimization method (Nelder & Mead, 1965) which is default of `optim` from the **stats** package, to examine the advantages of stochastic search against direct search.

$$f(x_1, x_2) = (x_1^2 + x_2 - 11)^2 + (x_1 + x_2^2 - 7)^2 \tag{5.2}$$

We performed 10,000 repetitions with each function in order investigate quality and speed of the solutions using parameters for relatively simple optimization problems for all examined methods. The optimizations were performed having the following parameters:

```
# stats package: optim (NM)
stats::optim(fn = hi, par = c(10, 10), method = "Nelder-Mead")

# optimization package: optim_sa
optimization::optim_sa(fun = hi, start = (c(10, 10)), trace = TRUE,
lower = c(-40, -40), uppe r= c(40, 40),
control = list(t0 = 500, nlimit = 50,r = 0.85,
rf = 3, ac_acc = 0.1, dyn_rf = TRUE))

# stats package optim (SA)
stats::optim(fn = hi, par = c(10, 10), method = "SANN",
control = list(tmax = 500, reltol = 0.1, temp = 50, trace = TRUE))

# GenSA package: GenSA
GenSA::GenSA(fn = hi, par = c(10, 10), lower = c(-40, -40), upper = c(40, 40),
control = list(temperature = 50, nb.stop.improvement = 30, maxit = 500))
```

Since we have a multimodal optimization problem with multiple equal solutions, evaluation of solutions quality is composed of response accuracy and covariate combination. With fixed starting

Table 5.1: Relative frequencies of covariate combinations in % after optimization for the four examined methods. Number of repetitions: 10,000. We used the parameters given in the example,only the `trace` options was deactivated.

		Result (rounded)			
		{-2.8, 3.1}	{3.0, 2.0}	{3.6, -1.8}	{-3.8, -3.3}
Method	optim_sa	22.19	33.49	28.05	16.27
	optim (SA)	25.91	30.89	24.08	19.12
	GenSA	0.00	0.00	0.00	100.00
	optim (NM)	0.00	0.00	0.00	100.00

parameters, the methods should be able to find all possible solutions. We defined the problem to be solved with sufficient accuracy when the response was ≤ 0.01. We also looked at the frequency distribution of the covariate combination after minimization. Subsequent to investigation of quality, we also compared the efficiencies by measuring calculation times using **microbenchmark** and the iterations frequencies.

It became clear that parameterization of NM was quite easy. It only needed a vector with starting values. The other functions needed much more settings. With view to accuracy each method performed well. All functions returned in mean of 10,000 calls responses with values $\leq$ 0.01. With view to frequency distribution, the functions performed different (Table 5.1). `optim_sa` and `optim (SA)` returned each possible solutions. The combination {-3.8, -3.3} was consistently least frequent. `GenSA` and `optim (NM)`, however, solely returned {-3.8, -3.3}. Further investigation revealed the solutions of `GenSA` and `optim (NM)` to be sensitive of the starting values. If `GenSA` and `optim (NM)` were parameterized with randomly drawn starting values, all four results would have been possible. Advantage of `optim_sa` and `optim (SA)` against `GenSA` and `optim (NM)` is, in this example, thus its independence from starting values.

As all functions were practically able to minimize Equation 5.2, comparison of calculation times appears to be another important point for quality assessment. As expected, the direct search method `optim (NM)` was by far faster then all stochastic methods (Figure 5.1, left). The within-group ranking of stochastic methods revealed `GenSA` to be fastest. It was in average 3.5 times faster than `optim_sa`. The two functions able coping with equally valued optima (`optim (SA)` and `optim_sa`) were slower than `GenSA` (Table 5.1; Figure 5.1, left).

Another way of comparing algorithms efficiency is to examine the frequency of necessary iterations solving the optimization problem. Again, `optim (NM)` performed best (Figure 5.1, right). While `optim_sa` and `GenSA` showed in average roughly the same numbers of iterations, `optim (SA)` needed by far most repetitions. Only `optim_sa` showed varying frequencies because `optim_sa` was, given the displayed parameters, the only function where the inner loop broke due to the threshold accepting criterion. It could be seen that `optim_sa` performed good when compared to established SA based optimization functions. The calculation of valid parameter combinations (Algorithm 5.1, lines 7 to 15) leads to multiple function calls within one iteration. For this, one iteration of `optim_sa` can last longer than one iteration of the other methods. The `dyn_rf` which adopts the search domain dynamically to specific loss function on the one hand thus leads to longer calculation times on the other hand. Improved flexibility therefore again corresponds with longer calculation time.

To conclude, all functions were generally able to solve the problem. The flexible stochastic search-grid of `optim (SA)` and `optim_sa` enabled archiving each of the four solutions. Practically, in case users are in doubt whether a problem has multiple solutions with equal responses, `optim (SA)` and `optim_sa` can simply be repeated without re-parameterization. If well-specified, they will return all possible solutions. They are thus advantageous for complex multimodal problems of that kind on the one hand, but slower on the other hand. Due to the multiple additional options, which all have to be called in the code, `optim_sa` is slowest. This example clearly reveals that higher flexibility and generality leads to significantly higher calculation times. Specific algorithms are advantageous for complexer problems while more general functions are useful for optimization problems with simple responses.

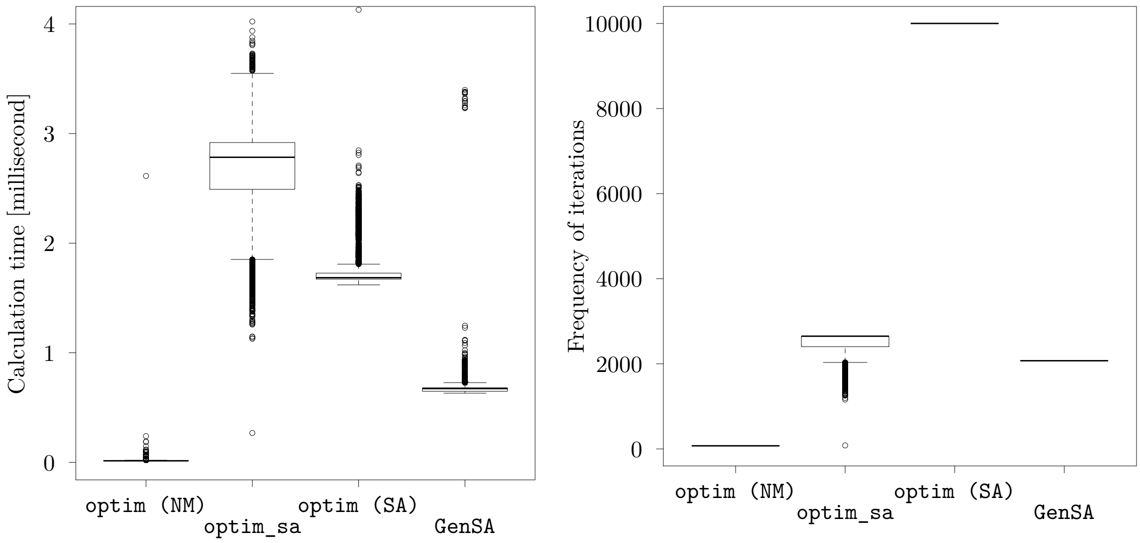

Figure 5.1: Calculation times and frequancy of iterations of the four examined optimization algorithms in Example 1. Note that the y-axis of the left diagram is truncated. `optim_sa` sowed 101 and `optim (SA)` 70 outliers between four and seven milliseconds. The frequency of iterations represents the total number of iterations. thus, for the SA methods, all inner loops repetitions are counted.

5.3.2 Himmelblau Function with discrete parameter space

A second example illustrating the advantage of flexibly defining the parameter spaces also bases on the function by Himmelblau (1972). It is an exemplary optimization problem which cannot be solved with any other examined method. If a user is interested in integer covariate combinations only, simply rounding the solution is usually not satisfying since the solution could be non-feasible or non-optimal (Cardoso et al., 1997). The flexible variation function `vf` of our models allows searching for integer temporary solutions only and thus searching for the global integer solution. `vf` can be used to restrict the parameter space to the specific problem. The following simple example shows a variation rule for an exemplary integer programming problem. The simple `var_fun_int` from the example returns a vector of integer covariates varying in dimension of `vf` around the passed covariates `para_0`. The `fun_length` must be passed explicitly, although it is implicitly given by the length of `para_0` because it might help simplifying the function `vf`. Dependence of `rf` and `temp` can be implemented. Optimization problems do not always need a dynamic component. If `vf` need not be dynamic, i.e. if the stochastic part shall be fixed during the entire iterations, `temp` and `rf` can separately be disabled by passing `NA` for the respective parameter. If `vf` does not depend on `rf`, the option `dyn_rf` will not be useful any more. It should be disabled in such cases to save computation time.

```
# Define vf
var_fun_int <- function (para_0, fun_length, rf, temp = NA) {
        ret_var_fun <- para_0 + sample.int(rf, fun_length, replace = TRUE) *
        ((rbinom(fun_length, 1, 0.5) * -2) + 1)
        return (ret_var_fun)
}

# Call optim_sa
int_programming <- optimization::optim_sa(fun = hi, start = c(10, 10), trace = TRUE,
lower = c(-40, -40), upper=c(40, 40),
control = list(t0 = 500, nlimit = 50,
r = 0.85, rf = 3, ac_acc = 0.1,
dyn_rf = TRUE, vf = var_func_int))
```

Calling the minimization function times leaded to the only integer solution $\{3, 2\}$. The generic plot function of `optimization` (Figure 5.2) helps interpreting the convergence and thus the solution quality as well as the algorithm behavior. Since the example is 2-dimensional, a `contour_plot` (Figure 5.2. right) could be created. It shows the state space of the Himmelblau function in continuously changing colors for parameter spaces between -4 and 4. The results at the end of each outer loop iteration are shown as points within the parameter space. It became obvious that only integer covariate combinations were calculated during the entire optimization (Figure 5.2, right). Figure 5.2 additionally helps explaining the stochastic part of the SA method. It becomes clear that though response of iteration 10 (parameter combination $\{0, 0\}$) was already quite near 0, following iteration ended with a relatively worse intermediate results. With response > 100, iteration 19 (parameter combination $\{2, 3\text{-}\}$) was much worse than iteration 12. The likelihood of keeping worse solutions shrank over time till it became practically 0 after iteration 40 (Figure 5.2, left). For problems of such kind, 40 iterations therefore should be far enough. This information could help the user parameterizing the function for the next problem.

`optim (SA)` also provides possibility of defining a variation function via the `gr`. Using the variation function from the example code with fixed `rf`, however, it was not possible to define robust parameters for solving an integer programming problem. `optim_sa` is thus advantageous against all other examined functions when the parameter space of the optimization problem underlies extended restrictions. It is the only function that enables global optimum integer search. To archive this, the user must define a changing rule in form of a R function. Users must thus examine their optimization problem very carefully and translate it into suitable functions. Parameterization of `optim_sa` is quite complex and time extensive but enables adopting the optimizer to problem specific needs. Other restrictions such as mixed integer problems may be defined analogously. `vf` can thus be used to flexibly restrict the parameter space. Further hints for interpretation can be found in the package documentation.

5.3.3 Structural vector autoregressive models with least dependent innovations

Vector autoregressive (VAR) models are used to examine dynamic structures of several time series endogenously within one model. Usually, impulse response functions come to use for investigating the between-series relationships. Those compositions, however, are not unique. The interactions between the time series variables in a VAR model are hence not directly calculable. The idea behind *structural* VAR (SVAR) is to define strategies to overcome the problem and enable unique impulse response definitions (Lütkepohl, 2006).

Least dependent innovations is one of plenty possibilities to obtain unique decompositions of the

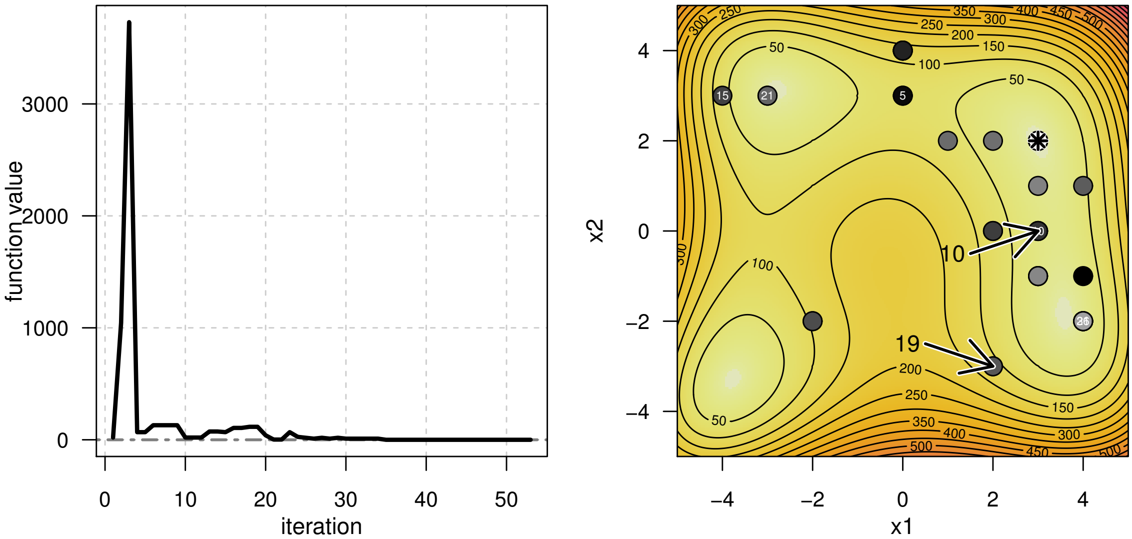

Figure 5.2: Exemplary examination plots created with the generic plot function. The left diagram shows the current optimal response over iteration of the outer loop. The left diagram displays the succession of the covariate values. The star points the covariate combination at optimum. The actual parameter space of the optimization is reduced for presentation reasons.

covariance matrix. It is one strategy to generate unique orthogonalized impulse responses in a VAR model. The idea is to minimize a Cramer-von-Mises test statistic for stochastically independent structural errors (Genest et al., 2007). Basically, a vector of $K(K-1)/2$ rotation angles between 0 and 2π, is modified until the stochastically independent structural errors become minimal. K is the number of time series in the SVAR model. An advantage of this method is, that it is very liberal in sense of distribution assumptions (Herwartz, 2014).

However, optimizing the test statistic is challenging, because the loss function has a large and unpredictable number of local optima and an irregular state space. Moreover, the function shows a relatively broad parameter space with very sensitive responses. It often reacts dramatically to small changes in the rotation angles. One approach to solve the optimization problem is the *grid optimization* (Herwartz & Plödt, 2015). Grid optimization is, however, inefficient in large samples and – dependening on the step size – sometimes unable to find the global optimum. Monte Carlo simulations have shown that direct search and gradient based optimization algorithms usually fail to find the optimal rotation angles. Performing several direct search optimizations sequentially with randomly changing starting values can be lead to satisfying solutions. The strategy is, however, also very inefficient.

The irregular response pattern and the high demands on the solution precision are the main challenges. The combination of SA with the adaptive variation of the search seems to be promising for the optimization problem. The relatively broad parameter variation at the beginning of the optimization process should ensure adequate search-grid size while the stochastic component of the SA should be able to tackle the irregular responses. Dynamically decreasing parameter variation is particular advantageous for optimizing the rotation angles as sufficient parameter accuracy is crucial for the reliability of the solution.

Practical application of `optim_sa` revealed its advantages. Using parameterizations for low performance and high precision, e.g. an initial temperature of 100,000, a maximum number of

10,000 inner loops and temperature reductions between 0.7 and 0.9, it was still more efficient than all other investigated methods. Sensitivity analysis of exemplary optimization problems confirmed the general applicability of `optim_sa`. The function was able to find the actual global optimum sufficiently often.

5.3.4 Forest harvesting schedule optimization

Forestry is traditionally knowledge-based field with optimization playing only minor role. However popularity of optimization methods is steadily rising. While Linear Programs are nowadays used in some states, e.g. Finland (Redsven et al., 2012), stochastic optimization programs are quite novel in forestry for optimization of harvesting intensity (Kangas et al., 2015). Our function is integral part of the first stochastic optimization software of forest operation in Germany and one of the first softwares worldwide on single tree scale. Optimization of forest harvesting planning represents an interesting and innovative practical example where `optim_sa` is recently used. **optimization** is part of the WaldPlaner based decision support software for forest enterprises by Hansen & Nagel (2014). WaldPlaner is a user front end for *Tree Growth Open Source Software* (TreeGrOSS) which is a complex Java written tree growth and yield simulation software used to forecast the developments of forest management areas (stands). It is a tool able to simulate forest enterprises with hundreds of forest stands simultaneously where the smallest simulation element is the single tree. Each tree in the system is thus simulated individually. Optimization of forest activities is accordingly not trivial since TreeGrOSS is a complex network of rules and functions which are predominantly nonlinear. The entire optimization process is composed of TreeGrOSS, **optimization** and a data warehouse. This multi-factorial composition implies high demand for flexibility of the optimization function. Loss function, which represents in this example the interface between the three elements of the optimization system, must be composed of R, Java (using **rJava**) and SQL (using **RPostgreSQL**). Main tasks of the interface are enabling communication between TreeGrOSS and optimization algorithm and rating the TreeGrOSS output in terms of costs and revenue such that the TreeGrOSS output is translated into a response readable by the optimization algorithm. Flexibility of loss and variation functions is hence a prerequisite for forest harvesting schedule optimization via TreeGrOSS simulations. Each loss function call causes a TreeGrOSS simulation and a database operation. In order to save time, parts of the loss are therefore programmed parallel. The response is, accordingly, nonlinear and particularly non-continuous. Random search methods are of therefore favorable for the problem. Obligatory sustainability of forest stand treatment is also considered in form of restrictions. Each function call returns, next to the actual response, a sustainability index. This index is used to restrict the optimization by simply defining `NA` responses whenever sustainability is violated.

It showed that forest treatment optimization was actually possible using **optimization**. We developed a loss function able translating the TreeGrOSS in- and output into interpretable variables for `optim_sa`. Sensitivity analysis using an exemplary forest enterprise comprised of five forest stands, with known global maximum, reinforced reliability of `optim_sa` for harvesting optimization. A solution sufficiently near the global maximum was found in arguable time on a standard personal computer. To test the practical usability, the optimization system was additionally tested on a real forest enterprise with 100 forest stands. The problem was solved within twelve hours using a cluster computer. Repeating the optimization three times leaded to equal responses but different harvesting volumes (thus covariate combinations). This again reveals the complexity of the problem and further reinforces the need for specific stochastic methods.

5.4 Discussion and outlook

All in all SA methods are advantageous compared to classical optimization procedures, if the loss function is non-linear and multimodal. Our simulated annealing approach optimizes these functions quite well. It might not be faster than the standard simulated annealing approach of the **stats** package, but therefore it was not designed. However, due to the shrinkage of the parameter space and the extra stopping criteria it manages to need less steps than the standard approach. Moreover the main advantage of our new approach is to be able to deal with irregular parameter spaces, as well as with non-continuous and sophisticated loss functions, where the standard approach is reaches its limits. In our examples we show that problems with these characteristics exists and that our algorithm solves these problems. Furthermore there are several examples of loss functions in natural science where some combinations of variables are restricted and our approach shows its benefits.

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Chapter 6

Conclusions

The thesis aims on evaluation, development and application of proper methods to strengthen the raw material supply of a growing bio-economy sector. It showed up that the success of a bio-based companies does, not least, depend on decisions that are made by foresters. Supporting forest management decisions is therefore beneficial not only for the forest sector itself but also for the wood processing companies. If forest enterprises and bio-economy companies were not able to contractually agree on continuous wood supply amounts, the success of a promising innovative bio-economy sector might be endangered. Forest decision-makers must therefore decide about the distribution of the available wood potential very carefully as the downstream value creation process of the wood processing sector is much higher than the value creation in the forest sector itself (El-Chichakli et al., 2016, p. 221,223). In a scenario of wood scarcity, distribution decisions can have substantial consequences for the wood processing companies which depend on wood as raw material. This reinforces the importance of DSS in the forest management decision process as they can be used to structure the entire planning process of wood distribution into solvable sub-problems (Pretzsch et al., 2008, p. 1065-1067). The benefits, disadvantages and findings of the distinct developed statistical models for decision support are discussed in the following.

6.1 Findings of the thesis

The introductory stated hypothesis, that matching demands of the rising bio-economy is actually problematic, was verified in chapter 2. Scarcity of woody biomass and the high complexity of the entire wood supply chain are problems forest enterprises and bio-economy companies have to cope with. The descriptive analysis of the recent wood potential and the wood usage reveals significance of the research question and thus confirms the need for profound systems to support the expected raw wood distribution problem. After the relevance of the introduction question is confirmed in chapter 2, the normative analysis in chapters 3 to 5 examine particular rationales why decision-makers may not exploit the wood potential fully and how optimal potentials could be calculated.

6.1.1 Analyzing status and development of raw wood availability in the European beech-dominated central Germany

The available wood potential of all European beech wood assortments was almost completely used in the period between 2002 and 2012 in central Germany (chapter 2). Though the European beech wood potential is expected to rise due to the ongoing forest development programs, the competition situation on the wood market will probably rise. The only perspective for upcoming bio-economy companies to establish on the wood market is hence to get in competition with existing market participants. A detailed analyses of the wood market is therefore a prerequisite for the success of wood processing companies.

The added value of stem wood is higher than those of any other assortment (Nagel & Spellmann, 2008). The stem wood supply is recently entirely exhausted by long-established wood processing companies. It is therefore very difficult for novel companies to establish immediately on the stem wood market. The share of smaller, low-valued European beech wood assortments is about 60 % (chapter 2). Although this low-valued wood is recently almost entirely used as well, it seems to be partially reachable in future. Approximately half of the wood potential in smaller dimensions is directly used energetically. If a bio-economy company is able to compete with the industrial wood and firewood prices, a solid base of renewable biomass from forests will be at disposal. This would be beneficial for the forest sector as well because the added value of sorting would increase (Möhring, 1997, p. 67).

Two lessons should be learned from the predicted wood scarcity. First of all, the sustainable reachable wood potential should be estimated as accurate as possible in order to investigate sources properly. Accurate estimations may uncover recently unused resources. Secondly, it should be ensured that the available potential is distributed thoroughly with view to the actual situation and also to the consequences.

6.1.2 Biomass functions and nutrient contents of European beech, oak, sycamore maple and ash and their meaning for the biomass supply chain

The findings from chapter 3 can improve gathering the complete biomass potential of mixed broadleaf forest sites. Comparison of several existing models revealed that estimation accuracy of biomass and nutrient contents in mixed broadleaf tree species sites can be significantly improved by the introduced models. This might help gathering formerly unused potential. The essay is particular relevant for the bio-based sector as innovative productions often require biomass from broadleaf tree species (Auer et al., 2016, p. 1) and the frequency of mixed broadleaf stands steadily increases (TI, 2014). The models enhance the accuracy of tree-specific biomass estimations. They can thus strengthen planning accuracy of entire biomass supply chains.

6.1.3 Modelling the economically viable wood in the crown of European beech trees

The models from chapter 4 aim on the assessment of the optimal wood volume in the crowns of European beech. They can hence be used to predict the full economically viable potential of smaller wood assortments. Allometric analysis revealed great wood potentials in the crowns of broadleaf trees. It is therefore essential to consider the predicted wood volume from the crown as a by-product of stem wood production. As the dimension of the wood assortments plays a minor role for many activities (subsection 1.6.2), gathering further wood potential from broadleaf crowns seems to be interesting for bio-economy companies. The models also allow a precise prediction of harvestable wood volume prior harvesting. They can therefore enhance the forecasting of volume flows in the biomass supply chain.

The model is able to calculate the maximal wood potential from an economic perspective only. It is therefore a purely normative-based model that predicts a rational rather than a realistic wood potential. Further economic or non-economic endogenous influences such as fixed assortments lengths or maximum small-end diameters cannot be considered in the model. It allows to calculate the maximal tree-specific wood amount but it does, of course, not predict actual decisions.

6.1.4 Flexible Global Optimization with Simulated-Annealing

Optimization of forest stands treatments offers opportunity to calculate forest operations with highest marginal return (chapter 5). The model can be used to calculate the full wood potential of an entire forest enterprise in a time period between 10 and 20 years. It is, in contrast to the other introduced models, a model for the support of intermediate-term decisions on a lager spatial scale. Amongst the calculation of the full economic wood potential, sensitivity analysis of different optimization scenarios seems to be interesting for planning purposes. If delivery agreements with upcoming bio-economy companies or any other recipient lead to opportunity costs, source providers must balance very carefully between advantages and drawbacks. The optimization model enables the calculation of those opportunity costs. The forest decision-maker can use the result to balance between the drawback of delivery contracts and their advantages in planning security. They can decide whether the benefits in intermediate-term planning justify the opportunity costs.

Furthermore, wood demander can use the results to calculate adequate wood prizes. The calculations can build an objective, evidence-based base for an agreement of intermediate-term binding wood prizes.

The combined simulation-optimization method implies high demands on the optimization algorithm (subsection 1.6.4). A robust optimization procedure is prerequisite for a reliable simulation-optimization model. It showed up that stochastic methods with dynamic random structures were able to cope with the specific needs of the combined simulation-optimization method. The favorable optimization is hence a composition of three optimization strategies (Corana et al., 1987; Kirkpatrick et al., 1983; Pronzato et al., 1984) which are all separately available as software packages. A composition of the two methods, however, is not published yet. Development of a specific software for optimization of forest thinning activities was straightforward. Intensive sensitivity analysis revealed the applicability and the efficiency of the package as optimization element in the simulation-optimization software.

6.2 Outlook

The next steps will be to implement the developed and evaluated models into proper software, providing the findings for scientists, students and practitioners. The WaldPlaner DSS provides a favorable front-end for the models as it is already established in forest science and practice.

One common aim of all introduced methods is the assessment of the full wood potential from economic perspective. All models provide decision support to strengthen the economic forest function. There are, however, numerous good reasons not to fully exploit the potentials. Conservation or recreational issues, which could decrease the actual harvestable wood volume, cannot be considered immediately. Combinations of the models from chapters 3 and 4 with DSS could enable consideration of other forest functions. Already existing forest DSS might reduce the wood potential due to conservation or recreational issues, thereby further enhancing the prediction accuracy of wood potentials. These aspects provide further arguments for an implementation of the introduced models into the WaldPlaner. WaldPlaner allows parametrization of different treatment options (Hansen & Nagel, 2014, p. 90-93). Nature conservation oriented treatments will obligatory have lower yields than economic oriented treatments. If any reasons permit full exploitation of the wood potential, WaldPlaner would forecast the limited yield.

The simulation-optimization software (chapter 5) optimizes the stand development with view to economic issues. Consideration of the other two forest function is nevertheless possible. As it was performed by Yousefpour & Hanewinkel (2009), conservation and recreational issues can be simplified such that they can be implemented as restrictions into the simulation-optimization software. Restrictions, e.g. harvesting permissions of old broadleaf trees or minimum standing volumes for specific stand ages, could be included to enhance the forecasting accuracy in forest stands with specific nature conservation regulations. The influence of wood quality on the optimal stand treatment is another relevant issue that could be examined with the simulation-optimization software. To achieve this, an interface with user-specific wood prizes must be implemented.

Cooperation between wood-processing companies as well as between companies and forest enterprises is the most important advantage of the bio-economy sector, where especially the assessment of throughout raw material supply chains appears to be interesting. The introduced methods in this thesis were developed to strengthen decisions in specific parts of supply chains in order to promote the cooperation of the forest and the bio-economy sector. The statistical methods, however, cover only small distinct parts of the supply chains. To enable meaningful cooperations, they must be somehow applicable for decision-makers in forestry as well as in bio-economy or logistic companies. When implementing the models into DSS, interfaces to other software will be mandatory to take their full advantages. A front-end with an interface to logistic DSS could link the optimized wood amounts with resource distribution simulations or optimizations.

Bibliography

Affleck, D. L. R. & Gregoire, T. G. (2015). Generalized and synthetic regression estimators for randomized branch sampling. *Forestry*, 88(5), 599–611.

Agostini, F. P., Soares-Pinto, D. D. O., Moret, M. A., Osthoff, C., & Pascutti, P. G. (2006). Generalized simulated annealing applied to protein folding studies. *Journal of computational chemistry*, 27(11), 1142–1155.

Akaike, H. (1981). Likelihood of a model and information criteria. *Journal of Econometrics*, 16, 3–14.

Albert, K., Annighöfer, P., Schumacher, J., & Ammer, C. (2014). Biomass equations for seven different tree species growing in coppice-with-standards forests in Central Germany. *Scandinavian Journal of Forest Research*, 29(3), 210–221.

Alberti, G., Candido, P., Peressotti, A., Turco, S., Piussi, P., & Zerbi, G. (2005). Aboveground biomass relationships for mixed ash (Fraxinus excelsior L. and Ulmus glabra Hudson) stands in Eastern Prealps of Friuli Venezia Giulia (Italy). *Annals of Forest Science*, 62(8), 831–836.

Altherr, E., Unfried, P., & Hrahetzky, V. (1978). *Statistische Rindenbeziehungen als Hilfsmittel zur Ausformung und Ausmessung unentrindeten Stammholzes*, volume 90 of *Mitteilungen der Forstlichen Versuchs- und Forschungsanstalt Baden-Würtemberg*. FVA Baden Württemberg.

Auer, V., Zscheile, M., Engler, B., Haller, P., Hartig, J., Wehnsener, J., Husmann, K., Erler, J., Thole, V., Schulz, T., Hesse, E., Rüther, N., & Himsel, A. (2016). BIOECONOMY CLUSTER: resource efficient creation of value from beech wood to bio-based building materials. In J. Eberhardsteiner, W. Winter, A. Fadai, & M. Pöll (Eds.), *World Conference on Timber Engineering (WCTE 2016)*. Wien: TU Wien.

Augusto, L., Ranger, J., Ponette, Q., & Rapp, M. (2000). Relationships between forest tree species, stand production and stand nutrient amount. *Annals of Forest Science*, 57(4), 12.

Barton, K. (2016). MuMIn: Multi-Model Inference.

Baskent, E. Z. & Jordan, G. A. (2002). Forest landscape management modeling using simulated annealing. *Forest Ecology and Management*, 165(1), 29–45.

Baskerville, G. (1972). Use of logarithmic regression in the estimation of plant biomass. *Canadian Journal of Forest Research*, 2(1), 49–53.

Bitz, M. (2005). *Vahlens Kompendium der Betriebswirtschaftslehre*, volume 2. Munich: Vahlen, 5 edition.

Block, J., Meiwes, K. J., Bachmann, G., König, W., & Utermann, J. (2013). Erhaltung der Produktivität der Waldböden bei der Holz- und Biomassenutzung. In *Bodenschutz - Ergänzbares Handbuch der Maßnahmen und Empfehlungen für Schutz, Pflege und Sanierung von Böden, Landschaft und Grundwasser*, volume 1. Lfg. /13 (pp. 1– 50).

Blum, C. & Roli, A. (2003). Metaheuristics in combinatorial optimization: Overview and conceptual comparison. *ACM Computing Surveys (CSUR)*, 35(3), 268–308.

BMEL (2011). *Waldstrategie 2020*. Bonn: Bundesministerium für Verbraucherschutz, Ernährung und Landwirtschaft. Bundesministerium für Ernährung, Landwirtschaft und Verbraucherschutz.

BMEL (2014a). *Der Wald in Deutschland - Ausgewählte Ergebnisse der dritten Bundeswaldinventur*. Berlin: Bundesministerium für Verbraucherschutz, Ernährung und Landwirtschaft.

BMEL (2014b). *Nationale Politikstrategie Bioökonomie - Nachwachsende Ressourcen und biotechnologische Verfahren als Basis für Ernährung, Industrie und Energie*. Berlin: Bundesministerium für Ernährung und Landwirtschaft.

BMEL (2016). *Wald und Rohholzpotenzial der nächsten 40 Jahre - Ausgewählte Ergebnisse der Waldentwicklungs- und Holzaufkommensmodellierung 2013 bis 2052*. Berlin. Bundesministerium für Ernährung, Landwirtschaft und Verbraucherschutz.

BMU (2007). *National Strategy on Biological Diversity*. Berlin: Federal Ministry for the Environment, Nature Conservation and Nuclear Safety.

Bonyad, A. E., Sima, A., Bakhshandeh, A., & H., D. (2012). Evaluation of non-destructive Meyer method for determination of bark volume of beech (Fagus orientalis Lipsky) in different geographical aspects. *Caspian Journal of Environmental Sciences*, 10(1), 67–73.

Boston, K. & Bettinger, P. (1999). An analysis of monte carlo integer programming, simulated annealing, and tabu search heuristics for solving spatial harvest scheduling problems. *Forest science*, 45(2), 292–301.

Bunce, R. G. H. (1968). Biomass and Production of Trees in a Mixed Deciduous Woodland: I. Girth and Height as Parameters for the Estimation of Tree Dry Weight. *Journal of Ecology*, 56(3), 759–775.

Böckmann, T. (2004). Forsteinrichtung - als Institution effektiv und unverzichtbar. *Allgemeine Forst und Jagdzeitung*, 175, 156–162.

Cancino, J. & Saborowski, J. (2005). Comparison of randomized branch sampling with and without replacement at the first stage. *Silva Fennica*, 39(2), 201–216.

Cardoso, M. F., Salcedo, R., de Azevedo, S. F., & Barbosa, D. (1997). A simulated annealing approach to the solution of minlp problems. *Computers & chemical engineering*, 21(12), 1349–1364.

Cerny, M. (1990). Biomass of Picea abies (L.) Karst. in midwestern Bohemia. *Scandinavian Journal of Forest Research*, 5(1-4), 83–95.

Chambers, J. M. & Hastie, T. J. (1992). *Statistical models in S*. Boca Raton, Fla.: Chapman & Hall/CRC.

Churchman, C. W., Ackoff, R. L., & Arnoff, E. L. (1957). *Introduction to operations research*. New York, London: John Wiley & Sons, Inc., Chapman & Hall, Ltd., accessed via http://archive.org/details/introductiontoo00chur on 4 April 2017.

Cienciala, E., Apltauer, J., Cerny, M., & Exnerová, Z. (2005). Biomass functions applicable for European beech. *Journal of Forest Science*, 51(4), 147–154.

Clarke, G. & Wright, J. W. (1964). Scheduling of vehicles from a central depot to a number of delivery points. *Operations research*, 12(4), 568–581.

Corana, A., Marchesi, M., Martini, C., & Ridella, S. (1987). Minimizing multimodal functions of continuous variables with the 'simulated annealing' algorithm. *ACM Trans. Math. Softw.*, 13(3), 262–280.

Dantzig, G. B., Fulkerson, D. R., & Johnson, S. M. (1959). On a linear-programming, combinatorial approach to the traveling-salesman problem. *Operations Research*, 7(1), 58–66.

Davis, L. S., Johnson, K. N., Bettinger, P., & Howard, T. E. (2001). *Forest Management: To Sustain Ecological, Economic, and Social Values.* New York: McGraw-Hill Higher Education, 4 edition.

de Besi, M. & McCormick, K. (2015). Towards a Bioeconomy in Europe: National, Regional and Industrial Strategies. *Sustainability*, 7(8), 10461–10478.

Degenhard, M. (2016). Holzmarkt - Schnittholznachfrage stabilisiert.

DeSarbo, W. S., Oliver, R. L., & Rangaswamy, A. (1989). A simulated annealing methodology for clusterwise linear regression. *Psychometrika*, 54(4), 707–736.

DESTATIS (2016). Statistisches Bundesamt Deutschland - GENESIS-Online.

DiCiccio, T. J. & Efron, B. (1996). Bootstrap confidence intervals. *Statistical Science*, 11(3), 189–228.

Dueck, G. & Scheuer, T. (1990). Threshold accepting: a general purpose optimization algorithm appearing superior to simulated annealing. *Journal of computational physics*, 90(1), 161–175.

Eckmüllner, O. (2006). Allometric relations to estimate needle and branch mass of Norway spruce and Scots pine in Austria. *Austrian Journal of Forest Science*, 123(1-2), 7–15.

Efken, J., Banse, M., Rothe, A., Dieter, M., Dirksmeyer, W., Ebeling, M., Fluck, K., Hansen, H., Kreins, P., Seintsch, B., & others (2012). *Volkswirtschaftliche Bedeutung der biobasierten Wirtschaft in Deutschland.* Technical report, Arbeitsberichte aus der vTI-Agrarökonomie.

Ekman, A., Campos, M., Lindahl, S., Co, M., Börjesson, P., Karlsson, E. N., & Turner, C. (2013). Bioresource utilisation by sustainable technologies in new value-added biorefinery concepts - two case studies from food and forest industry. *Journal of Cleaner Production*, 57, 46–58.

El-Chichakli, B., von Braun, J., Lang, C., Barben, D., & Philp, J. (2016). Policy: Five cornerstones of a global bioeconomy. *Nature News*, 535(7611), 221.

FACG (2014). Shapefile Germany with federal states. Federal Agency for Cartography and Geodesy.

FANC (2010). Map of potential natural vegetation in Germany. Federal Agency for Nature Conservation.

Fischer, C. & Husmann, K. (2016). Flächen-Übergangsmatrizen als erweiterte Auswertung der Bundeswaldinventur: Darstellung am Beispiel der Veränderung der Bestockungszusammensetzung in Niedersachsen (under review). *Allgemeine Forst- und Jagdzeitung.*

Gaffrey, D. & Saborowski, J. (1999). RBS, ein mehrstufiges Inventurverfahren zur Schätzung von Baummerkmalen - I. Schätzung von Nadel- und Asttrockenmassen bei 66-jährigen Douglasien. *Allgemeine Forst- und Jagdzeitung*, 170. Jg 10-11, 177–183.

Gauer, J. (2012). *Waldökologische Naturräume Deutschlands - Forstliche Wuchsgebiete und Wuchsbezirke*. Braunschweig: Thünen Institut.

Geiger, C. & Kanzow, C. (1999). Das nelder-mead-verfahren. *Numerische Verfahren zur Lösung unregestrierter Optimierungsaufgaben*.

Geldermann, J., Kolbe, L. M., Krause, A., Mai, C., Militz, H., Osburg, V.-S., Schöbel, A., Schumann, M., Toporowski, W., & Westphal, S. (2016). Improved resource efficiency and cascading utilisation of renewable materials. *Journal of Cleaner Production*, 110, 1–8.

Genest, C., Quessy, J.-F., & Remillard, B. (2007). Asymptotic local efficiency of cramer-von mises tests for multivariate independence. *The Annals of Statistics*.

Genet, A., Wernsdörfer, H., Jonard, M., Pretzsch, H., Rauch, M., Ponette, Q., Nys, C., Legout, A., Ranger, J., Vallet, P., & Saint-Andre, L. (2011). Ontogeny partly explains the apparent heterogeneity of published biomass equations for Fagus sylvatica in central Europe. *Forest Ecology and Management*, 261(7), 1188–1202.

Goffe, W. L. et al. (1996). Simann: A global optimization algorithm using simulated annealing. *Studies in Nonlinear Dynamics and Econometrics*, 1(3), 169–176.

Gorry, G. A. & Morton, M. S. S. (1971). A framework for management information systems. In *Sloan Management Review*, volume 13 (pp. 21–30). Massachusetts: Massachusetts Institute of Technology.

Graham, M. H. (2003). Confronting multicollinearity in ecological multiple regression. *Ecology*, 84(11), 2809–2815.

Gregoire, T. G. & Valentine, H. (2008). *Sampling Strategies for Natural Ressources and the Environment*. Chapman & Hall/CRC. Boca Raton, London, New York.

Gregoire, T. G., Valentine, H. T., & Furnival, G. M. (1995). Sampling Methods to Estimate Foliage and Other Characteristics of Individual Trees. *Ecology*, 76(4), 1181.

Grote, R., Schuck, J., Block, J., & Pretzsch, H. (2003). Oberirdische holzige Biomasse in Kiefern-/Buchen- und Eichen-/Buchen-Mischbeständen. *Forstwissenschaftliches Centralblatt*, 122(5), 287–301.

Gruber, F., Mann, T. E., Kuhr, M., & Eichhorn, J. (2004). Kronenwachstum von Rotbuchen (Fagus sylvatica L.) in Abhängigkeit von der Witterung auf einem kalkbeeinflussten Basaltstandort Zierenberg. *Allgemein Forst- und Jagdzeitung*, 175, 70–77.

Haarhaus, M. (2012). *AfL-Info 12/13. Richtpreise, Tarife, Kalkulationen, Adressen*. Wiegersen-Sauensiek.

Hansen, J., Ludwig, A., Spellmann, H., Nagel, J., Möhring, B., von Lüpke, N., & Schmidt-Walter, P. (2008). *Rohholzpotenziale und ihre Verfügbarkeit in Hessen*. Veröffentlichungen der NW-FVA und der Abteilung für Forstökonomie der Georg-August-Universität Universität Göttingen. Göttingen: NW-FVA.

Hansen, J. & Nagel, J. (2014). *Waldwachstumskundliche Softwaresysteme auf Basis von TreeGrOSS-Anwendung und theoretische Grundlagen*. Göttingen: Niedersächsische Staats-und Universitätsbibliothek.

Hansen, J. H. (2012). *Modellbasierte Entscheidungsunterstützung für den Forstbetrieb: Optimierung kurzfristiger Nutzungsoptionen und mittelfristiger Strategien unter Verwendung metaheuristischer Verfahren und parallelen Rechnens*. Göttingen: Cuvillier, 1. aufl. edition.

Hempel, C. G. & Oppenheim, P. (1948). Studies in the Logic of Explanation. *Philosophy of Science*, 15(2), 135– 175.

Henderson, D. E., Jose, S., & others (2012). Nutrient use efficiency of three fast growing hardwood species across a resource gradient. *Open Journal of Forestry*, 2(04), 187.

Hennig, C., Brosowski, A., & Majer, S. (2016). Sustainable feedstock potential - a limitation for the bio-based economy? *Journal of Cleaner Production*, 123, 200–202.

Henningsen, A. & Hamann, J. D. (2007). systemfit: A Package for Estimating Systems of Simultaneous Equations in R. *Journal of Statistical Software*, 23(4), 1–40.

Herwartz, H. (2014). Structural analysis with independent innovations. *cege Discussion Papers*.

Herwartz, H. & Plödt, M. (2015). The macroeconomic effects of oil price shocks: Evidence from a statistical identification approach. *Journal of International Money and Finance*.

Hildebrandt, J., Bezama, A., & Thrän, D. (2014). Establishing a robust sustainability index for the assessment of bioeconomy regions. In *2014 International Conference and Utility Exhibition on Green Energy for Sustainable Development (ICUE)* (pp. 1–4).

Himmelblau, D. M. (1972). *Applied nonlinear programming*. McGraw-Hill Companies.

HMUKLV (2014). *Hessen - Bäume, Wälder, Lebensräume : ausgewählte Ergebnisse der dritten Bundeswaldinventur (BWI 3) für Hessen - Deutsche Digitale Bibliothek*. Wiesbaden: Hessisches Ministerium für Umwelt, Klimaschutz, Landwirtschaft und Verbraucherschutz.

Hochbichler, E., Bellos, P., & Lick, E. (2006). Biomass functions for estimating needle and branch biomass of spruce (Picea abies) and Scots pine (Pinus sylvestris) and branch biomass of beech (Fagus sylvatica) and oak (Quercus robur and petraea). *Centralblatt für das gesamte Forstwesen (Austrian Journal of Forest Sciences)*, (123), 35–46.

Hoganson, H. M. & Meyer, N. G. (2015). Constrained Optimization for Addressing Forest-Wide Timber Production. *Current Forestry Reports*, 1(1), 33–43.

How, B. S., Tan, K. Y., & Lam, H. L. (2016). Transportation decision tool for optimisation of integrated biomass flow with vehicle capacity constraints. *Journal of Cleaner Production*.

Hurmekoski, E. & Hetemäki, L. (2013). Studying the future of the forest sector: Review and implications for long-term outlook studies. *Forest Policy and Economics*, 34, 17–29.

Hutcheson, G. D. & Moutinho, L. (2008). *Statistical Modeling for Management*. London: SAGE Publications.

Huxley, J. (1932). *Problems of relative growth*. New York: Dial Press.

Ingber, L. (1993). Simulated annealing: Practice versus theory. *Mathematical and computer modelling*, 18(11), 29–57.

Ingrao, C., Bacenetti, J., Bezama, A., Blok, V., Geldermann, J., Goglio, P., Koukios, E. G., Lindner, M., Nemecek, T., Siracusa, V., Zabaniotou, A., & Huisingh, D. (2016). Agricultural and forest biomass for food, materials and energy: bio-economy as the cornerstone to cleaner production and more sustainable consumption patterns for accelerating the transition towards equitable, sustainable, post fossil-carbon societies. *Journal of Cleaner Production*, 117, 4–6.

Jacobsen, C., Rademacher, P., Meesenburg, H., & Meiwes, K. J. (2003). *Gehalte chemischer Elemente in Baumkompartimenten: Literaturstudie und Datensammlung*, volume B69.

Jessen, R. J. (1955). Determining the Fruit Count on a Tree by Randomized Branch Sampling. *Biometrics*, 11(1), 99–109. ArticleType: research-article / Full publication date: Mar., 1955 / Copyright © 1955 International Biometric Society.

Joosten, R. & Schulte, A. (2003). Schätzung der Nährstoffexporte bei einer intensivierten Holznutzung in Buchenwäldern (Fagus sylvatica). *Allgemeine Forstund Jagdzeitung*, 174(9), 157–168.

Kangas, A., Kurttila, M., Hujala, T., Eyvindson, K., & Kangas, J. (2015). *Decision Support for Forest Management*. Number 30 in Managing Forest Ecosystems. Cham: Springer International Publishing, 2nd ed edition.

Keeney, R. L. (1982). Decision analysis: an overview. *Oper Res*, 30(5), 803–838.

Kirkpatrick, S., Gelatt, C. D., Vecchi, M. P., et al. (1983). Optimization by simulated annealing. *science*, 220(4598), 671–680.

Konopka, B., Pajtik, J., & Seben, V. (2015). Biomass functions and expansion factors for young trees of European ash and Sycamore maple in the Inner Western Carpathians. *Austrian Journal of Forest Science*, 132(1), 1–26.

Kuzelka, K. & Marusak, R. (2012). Spline representation of irregular and malformed stem profiles of broadleaved tree species in White Carpathian Mountains. *Beskydy*, 5(2), 111–120.

König, N. & Fortmann, H. (2012a). *Elementbestimmungsmethoden und Qualtätskontrollmethoden*. Number 80 in [Berichte der Sektion Waldökosystemforschung / B] Berichte der Sektion Waldökosystemforschung / Zentrum für Biodiversität und Nachhaltige Landnutzung (CBL) / Sektion Waldökosystemforschung. - Göttingen : CBL, Sektion Waldökosystemforschung, 2012-. Göttingen: Sektion Waldökosysteforschung der Univ. Göttingen.

König, N. & Fortmann, H. (2012b). *Probenvorbereitungsmethoden und Untersuchungsmethoden*. Number 79 in [Berichte der Sektion Waldökosystemforschung / B] Berichte der Sektion Waldökosystemforschung / Zentrum für Biodiversität und Nachhaltige Landnutzung (CBL) / Sektion Waldökosystemforschung. - Göttingen : CBL, Sektion Waldökosystemforschung, 2012-. Göttingen: Sektion Waldökosysteforschung der Univ. Göttingen.

Ledermann, T. & Neumann, M. (2006). Biomass equations from data of old long-term experimental plots. *Austrian Journal of Forest Science*, 1/2(123), 47– 64.

Lin, C., Haley, K., & Sparks, C. (1995). A comparative study of both standard and adaptive versions of threshold accepting and simulated annealing algorithms in three scheduling problems. *European Journal of Operational Research*, 83(2), 330–346.

Lütkepohl, H. (2006). Structural vector autoregressive analysis for cointegrated variables. In *Modern Econometric Analysis* (pp. 73–86). Springer.

Magee, L. (1990). R2 Measures Based on Wald and Likelihood Ratio Joint Significance Tests. *The American Statistician*, 44(3), 250–253.

Mantau, U. (2012). *Holzrohstoffbilanz Deutschland, Entwicklungen und Szenarien des Holzaufkommens und der Holzverwendung 1987 bis 2015*. Hamburg: Infro und Uni Hanburg.

Marklund, L. G. (1988). *Biomass functions for pine, spruce and birch in sweden*, volume 45 of *Department of Forest Survey Report*. Umea: Swedish University of Agricultural Sciences.

McCormick, K. & Kautto, N. (2013). The Bioeconomy in Europe: An Overview. *Sustainability*, 5(6), 2589–2608.

Meiwes, K. J., Rumpf, S., Klinck, U., & Meesenburg, H. (2012). Vollbaumnutzung: Untersuchungsergebnisse zum Nährelement-Export in Nordwestdeutschland und Ansätze zur standörtlichen Bewertung. *Deutscher Verband Forstlicher Forschungsanstalten Sektion Ertragskunde Jahrestagung 2012 Ottenstein*, (pp. 88–92).

Metropolis, N., Rosenbluth, A. W., Rosenbluth, M. N., Teller, A. H., & Teller, E. (1953). Equation of state calculations by fast computing machines. *The journal of chemical physics*, 21(6), 1087–1092.

MFACP (2004). *Langfristige ökologische Waldentwicklung- Richtlinie zur Baumartenwahl*, volume 54 of *Aus dem Walde - Schriftenreihe Waldentwicklung Niedersachsen*. Wolfenbüttel: Federal ministry of Food and Agriculture. Lower Saxony Ministry of Food, Agriculture and Consumer Protection.

Miettinen, J., Ollikainen, M., Nieminen, T. M., Ukonmaanaho, L., Laurén, A., Hynynen, J., Lehtonen, M., & Valsta, L. (2014). Whole-tree harvesting with stump removal versus stem-only harvesting in peatlands when water quality, biodiversity conservation and climate change mitigation matter. *Forest Policy and Economics*, 47, 25–35.

Mitscherlich, G. (1970). *Form und Wachstum von Baum und Bestand*. Frankfurt a.M.: Sauerländer.

ML (2004). *Langfristige ökologische Waldentwicklung- Richtlinie zur Baumartenwahl*, volume 54 of *Aus dem Walde - Schriftenreihe Waldentwicklung Niedersachsen*. Wolfenbüttel: Bundesministerium für Verbraucherschutz, Ernährung und Landwirtschaft. Niedersächsisches Ministerium für Ernährung, Landwirtschaft und Verbraucherschutz.

ML (2014). *Der Wald in Niedersachsen: Ergebnisse der Bundeswaldinventur 3*. Hannover: Niedersächsisches Ministerium für Ernährung, Landwirtschaft und Verbraucherschutz, 1 edition.

Muys, B., Hynynen, J., Palahi, M., Lexer, M. J., Fabrika, M., Pretzsch, H., Gillet, F., Briceño, E., Nabuurs, G.-J., & Kint, V. (2010). Simulation tools for decision support to adaptive forest management in Europe. *Forest Systems*, 19(0), 86–99.

Mußhoff, O. & Hirschauer, N. (2013). *Modernes Agrarmanagement: betriebswirtschaftliche Analyse- und Planungsverfahren*. München: Vahlen, 3., überarb. und erw. aufl. edition.

Möhring, B. (1997). Betriebswirtschaftliche Probleme und Chancen. *AFZ/ Der Wald*, 2, 67– 71.

Möhring, B. (2010). Optimierung forstlicher Produktion unter Beachtung von finanziellen Restriktionen | Optimisation of forest production under financial restrictions. *Schweizerische Zeitschrift fur Forstwesen*, 161(9), 346–354.

Möller, W. (2007). *Umweltrecht - Planung, Wald, Naturschutz, Jagd, Wasser, Boden, Immissionen, Abfall u.a. - Kommentare: Bundesrecht und exemplarisch niedersächsisches Landesrecht - mit verbundenem Nutzungsrecht, Europarecht*. Selbstverlag des Autors, 4b., überarb. u. erw. aufl. edition.

Müller-Using, B. & Rademacher, P. (2004). Bioelemententzüge bei der Holznutzung in Rein- und Mischbeständen aus Buche und Fichte. In *Berichte des Forschungszentrums Waldökosysteme*, volume Band 71 of *Reihe B* (pp. 81–110). Göttingen.

Nagel, J. (1996). Anwendungsprogramm zur bestandesbewertung und zur prognose der bestandesentwicklung. *Forst und Holz*, 51(3), 76–78.

Nagel, J. (2009). Waldwachstumssimulation mit dem Java Software Paket TreeGrOSS- Neuerungen, Erweiterungsmöglichkeiten und Qualitätsmamagement. In *Tagungsband der gemainsamen Jahrestagung der Sektion Forstliche Biometrie und Informatik im DVFFA (20. Tagung) und der AG Ökologie u. Umwelt in der Intern. Biometrie Gesellschaft*, Die Grüne Reihe (pp. 174– 178). Nordwestdeutsche Forstliche Versuchsanstalt.

Nagel, R.-V. & Spellmann, H. (2008). Wachstum, Behandlung und Ertrag von Reinbeständen der Rotbuche (Fagus sylvatica L.) in Nordwestdeutschland. In *Ergebnisse angewandter Forschung zur Buche*, volume 3 of *Beiträge aus der Nordwestdeutschen Forstlichen Versuchsanstalt* (pp. 221– 265). Göttingen: Universitätsverlag Göttingen.

Nash, J. C. et al. (2014). On best practice optimization methods in r. *Journal of Statistical Software*, 60(i02).

Nelder, J. & Mead, R. (1965). A simplex method for function minimization. *Computer Journal*, 7(4), 308–313.

Neumann-Spallart, O. (1952). *Das Stückmassegesetz nach Hilf in mathematischer Beleuchtung.* Wien.

Niklas, K. J. (1994). *Plant allometry: the scaling of form and process.* Chicago [u.a.]: Univ. of Chicago Press.

Ochs, T., Duschl, C., & Seintsch, B. (2007). Struktur und Rohstoffbedarf der Holzwirtschaft. *Holz-Zentralblatt*, 133(12), 269–271.

Ollikainen, M. (2014). Forestry in bioeconomy – smart green growth for the humankind. *Scandinavian Journal of Forest Research*, 29(4), 360–366.

Parresol, B. R. (2001). Additivity of nonlinear biomass equations. *Canadian Journal of Forest Research*, 31(5), 865–878.

Pretzsch, H. (2010). Re-Evaluation of Allometry: State-of-the-Art and Perspective Regarding Individuals and Stands of Woody Plants. In U. Lüttge, W. Beyschlag, B. Büdel, & D. Francis (Eds.), *Progress in Botany 71*, number 71 in Progress in Botany (pp. 339–369). Springer Berlin Heidelberg.

Pretzsch, H., Block, J., Dieler, J., Gauer, J., Göttlein, A., Moshammer, R., Schuck, J., Weis, W., & Wunn, U. (2014). Nährstoffentzüge durch die Holz-und Biomassenutzung in Wäldern. Teil 1: Schätzfunktionen für Biomasse und Nährelemente und ihre Anwendung in Szenariorechnungen. *Allgemeine Forst- und Jagdzeitung*, (185), 261–285.

Pretzsch, H. & Dieler, J. (2012). Evidence of variant intra- and interspecific scaling of tree crown structure and relevance for allometric theory. *Oecologia*, 169(3), 637–649.

Pretzsch, H., Grote, R., Reineking, B., Rötzer, T., & Seifert, S. (2008). Models for Forest Ecosystem Management: A European Perspective. *Annals of Botany*, 101(8), 1065–1087.

Pronzato, L., Walter, E., Venot, A., & Lebruchec, J.-F. (1984). A general-purpose global optimizer: Implimentation and applications. *Mathematics and Computers in Simulation*, 26(5), 412–422.

R Core Team (2016). *R: A Language and Environment for Statistical Computing.* Vienna, Austria: R Foundation for Statistical Computing.

Rademacher, P., Schönfelder, E., & Meiwes, K. J. (2011). Elementgehalte in Baumkompartimenten von Fichte, Kiefer, Buche, Eiche und Douglasie. In *Forschungsvorhaben: Möglichkeiten und Grenzen der Vollbaumnutzung. Ergebnisbericht (FKZ: 22015407)* (pp. 125– 154). Göttingen: Fachagentur für Nachwachsende Rohstoffe des Bundesministeriums für Ernährung, Landwirtschaft und Verbraucherschutz.

Redsven, V., Hirvelä, H., Härkönen, K., Salminen, O., & Siitonen, M. (2012). *MELA2012 Reference Manual (2nd edition).* The Finnish Forest Research Institute.

Reynolds, K. M., Twery, M., Lexer, M. J., Vacik, H., Ray, D., Shao, G., & Borges, J. G. (2008). Decision Support Systems in Forest Management. In *Handbook on Decision Support Systems 2*, International Handbooks Information System (pp. 499–533). Springer Berlin Heidelberg. DOI: 10.1007/978-3-540-48716-6_24.

Roloff, A. (1986). *Morphologie der Kronenentwicklung von Fagus sylvatica L. (Rotbuche) unter besonderer Berücksichtigung möglicherweise neuartiger Veränderungen.* Berichte des Forschungszentrums Waldökosysteme, Waldsterben / Forschungszentrum Waldökosysteme, Waldsterben, Göttingen. Göttingen: Forschungszentrum Waldökosysteme, Waldsterben.

Rumpf, S., Nagel, J., & Schmidt, M. (2011). Biomasseschätzfunktionen von Fichte, Kiefer, Buche Eiche und Douglasie für Nordwestdeutschland. In *Forschungsvorhaben: Möglichkeiten und Grenzen der Vollbaumnutzung. Ergebnisbericht (FKZ: 22015407)* (pp. 25– 124). Göttingen: Fachagentur für Nachwachsende Rohstoffe des Bundesministeriums für Ernährung, Landwirtschaft und Verbraucherschutz.

Rüther, B., Hansen, J., Ludwig, A., Spellmann, H., Nagel, J., Möhring, B., & Dieter, M. (2007). *Clusterstudie Forst und Holz Niedersachsen*, volume 1 of *Beiträge aus der Nordwestdeutschen Forstlichen Versuchsanstalt.* Göttingen: Universitätsdrucke Göttingen.

Saborowski, J. & Gaffrey, D. (1999). RBS, ein mehrstufiges Inventurverfahren zur Schätzung von Baummerkmalen - II. Modifizierte RBS-Verfahren. *Allgemein Forst- und Jagdzeitung*, (170. Jg 12), 223– 227.

Sanquetta, C. R., Behling, A., Corte, A. P. D., Netto, S. P., Schikowski, A. B., & Amaral, M. K. d. (2015). Simultaneous estimation as alternative to independent modeling of tree biomass. *Annals of Forest Science*, 72(8), 1099–1112.

Schmitz, F., Polley, H., Hennig, P., Dunger, K., & Schwitzgebel, F. (2008). *Die zweite Bundeswaldinventur BWI2. Inventur und Auswertungsmethoden zu den Bundeswaldinventuren 2001 bis 2002 und 1986 bis 1988.* Braunschweig: vTI (von Thünen Institut).

Schröter, M., Härdtle, W., & Oheimb, G. v. (2012). Crown plasticity and neighborhood interactions of European beech (Fagus sylvatica L.) in an old-growth forest. *European Journal of Forest Research*, 131(3), 787–798.

Shim, J. P., Warkentin, M., Courtney, J. F., Power, D. J., Sharda, R., & Carlsson, C. (2002). Past, present, and future of decision support technology. *Decision Support Systems*, 33(2), 111–126.

Simon, H. A. (1979). Rational Decision Making in Business Organizations. *The American Economic Review*, 69(4), 493–513.

Smith, R. J. (1993). Logarithmic transformation bias in allometry. *American Journal of Physical Anthropology*, 90(2), 215–228.

Speidel, G. (1972). *Planung im Forstbetrieb: Grundlagen und Methoden der Forsteinrichtung*. Hamburg, Berlin: Paul Parey.

Sprugel, D. G. (1983). Correcting for Bias in Log-Transformed Allometric Equations. *Ecology*, 64(1), 209–210. ArticleType: research-article / Full publication date: Feb., 1983 / Copyright © 1983 Ecological Society of America.

Stanovich, K. E. & West, R. F. (2000). Individual differences in reasoning: Implications for the rationality debate? *Behavioral and Brain Sciences*, 23(5), 645–665.

Starr, M. K. & Tapiero, C. S. (1975). Linear Breakeven Analysis Under Risk. *Operational Research Quarterly (1970-1977)*, 26(4), 847.

Stumpf, M. P. H. & Porter, M. A. (2012). Critical Truths About Power Laws. *Science*, 335(6069), 665–666.

Tabacchi, G., Cosmo, L. D., & Gasparini, P. (2011). Aboveground tree volume and phytomass prediction equations for forest species in Italy. *European Journal of Forest Research*, 130(6), 911–934.

Theussl, S. & Borchers, H. W. (2016). CRAN Task View: Optimization and Mathematical Programming.

Thurnher, C., Gerritzen, T., Maroschek, M., Lexer, M. J., & Hasenauer, H. (2013). Analysing different carbon estimation methods for Austrian forests Eine Analyse unterschiedlicher Kohlenstoffschätzmethoden für Wälder in Österreich. *Austrian Journal of Forest Science*, 3, 141–166.

TI (2014). Third National Forest Inventory - Database. https://bwi.info/. accessed: 13 January 2017.

Umeki, K. (1995). Importance of Crown Position and Morphological Plasticity in Competitive Interaction in a Population of Xanthium canadense. *Annals of Botany*, 75(3), 259–265.

United Nations General Assembly (2005). *2005 World Summit Outcome*. Number A/60/1. New York: Adopted by the General Assembly.

Valentine, H. T., Tritton, L. M., & Furnival, G. M. (1984). Subsampling Trees for Biomass, Volume, or Mineral Content. *Forest Science*, 30(3), 673–681.

Vallet, P., Dhôte, J.-F., Moguédec, G. L., Ravart, M., & Pignard, G. (2006). Development of total aboveground volume equations for seven important forest tree species in France. *Forest Ecology and Management*, 229(1-3), 98–110.

Varian, H. R. (2010). *Intermediate microeconomics : a modern approach*. New York, NY [u.a.]: Norton, 8. ed., internat. student ed. edition.

Venables, W. & Ripley, B. (2002). *Modern Applied Statistics with S*. New York: Springer, 4th edition.

Vitousek, P. (1982). Nutrient cycling and nutrient use efficiency. *American Naturalist*, (pp. 553–572).

Wacker, J. G. (1998). A definition of theory: research guidelines for different theory-building research methods in operations management. *Journal of Operations Management*, 16(4), 361–385.

Wagstaff, K., Rogers, S., Schroedl, S., & Cardie, C. (2001). Constrained K-Means clustering with background knowledge. *Proceedings of the 18th International Conference on Machine Learning*, (pp. 577– 584).

Warton, D. I., Duursma, R. A., Falster, D. S., & Taskinen, S. (2012). smatr 3- an R package for estimation and inference about allometric lines. *Methods in Ecology and Evolution*, 3(2), 257–259.

Wegener, I. (2005). Simulated annealing beats metropolis in combinatorial optimization. In *International Colloquium on Automata, Languages, and Programming* (pp. 589–601).: Springer.

Weis, W. & Göttlein, A. (2012). Nährstoffnachhaltige Biomassenutzung. *LWF Aktuell*, 90, 44–47.

West, G. B. (1999). The Fourth Dimension of Life: Fractal Geometry and Allometric Scaling of Organisms. *Science*, 284(5420), 1677–1679.

West, G. B., Brown, J. H., & Enquist, B. J. (1997). A General Model for the Origin of Allometric Scaling Laws in Biology. *Science*, 276(5309), 122–126.

Wilson, B. F. (2000). Apical control of branch growth and angle in woody plants. *American journal of botany*, 87(5), 601–607.

Wood, S. N. (2006). *Generalized Additive Models: An Introduction with R*. Chapman & Hall/CRC.

Wördehoff, R., Spellmann, H., Evers, J., & Nagel, J. (2011). *Kohlenstoffstudie Forst und Holz Niedersachsen*, volume 6 of *Beiträge aus der Nordwestdeutschen Forstlichen Versuchsanstalt*. Göttingen: Univ.-Verl. Göttingen.

Xiang, Y., Gubian, S., Suomela, B., & Hoeng, J. (2013). Generalized simulated annealing for global optimization: the gensa package. *The R Journal Volume 5(1):13-29, June 2013*.

Yousefpour, R. & Hanewinkel, M. (2009). Modelling of forest conversion planning with an adaptive simulation-optimization approach and simultaneous consideration of the values of timber, carbon and biodiversity. *Ecological Economics*, 68(6), 1711–1722.

Zianis, D., Muukonen, P., Mäkipää, R., & Mencuccini, M. (2005). *Biomass and stem volume equations for tree species in Europe*, volume 4. Finnish Society of Forest Science, Finnish Forest Research Institute.

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