AI for Optimal and Sustainable Forest Management

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Abstract

Forests are precious multi-use resources with high economic, ecologic, and societal value. Forests not only produce wood - a renewable resource that is increasingly replacing fossil-based materials - but also preserve biodiversity and sequestrate CO₂ from the atmosphere. Optimal forest management is therefore crucial for combating climate change and for reaching several of the United Nations' (UN) Sustainability Development Goals. However, determining optimal harvest timings and intensities is one of the oldest - and still unsolved - problems in forestry. Optimizing forest management operations presents a complex, dynamic, discrete-time control problem. Complications arise from discontinuities, nonconvexities, a large number of decision variables, a hybrid action space, and a long planning horizon. Conflicting stakeholder interests and uncertainty - for example in forest growth dynamics, timber prices, currency exchange rates, or natural disasters - further complicate the problem.

Existing forestry optimization methods need to either simplify the problem to remain feasible or they require days or even weeks to find an approximate solution. This leads to sub-optimal forest management decisions, which in turn lead to economic losses and unnecessary environmental destruction.

Against this backdrop, this doctoral dissertation contributes novel methods and insights on optimal and sustainable forest management by applying AI-based optimization techniques that have not been previously used in economic forest research. In Article I, we use multi-objective evolutionary algorithms to compute and evaluate multi-objective forestry strategies, without the need for policy makers to assign preferences a priori. Article II marks a methodological shift and explores the necessary preconditions for successful real-world application of reinforcement learning. In Article III, we then use reinforcement learning to solve a high-dimensional optimal harvesting problem that correctly includes stochasticity in forest growth and in the occurrence of natural disasters. Our method is the first to simultaneously consider both clear-cutting and continuous cover forest management, and to calculate near-optimal harvesting schedules purely based on the long-term goals of forest owners. We find that multi-species continuous cover forestry is often more profitable and sustainable than current single-species clear-cut practices; especially when including the risk of natural disasters. Moreover, our work helps to navigate conflicting goals (economic profit vs. carbon storage vs. biodiversity). Finally, we establishes forest management as a multi-disciplinary research area by bridging economic forest research with AI research.

In summary, this thesis contributes novel methods and practical insights on optimal and sustainable forest management, with far-reaching implications for forest owners, policy makers, asset managers, ESG investors, and for reaching several UN Sustainability Development Goals.

Keywords AI, forest management, optimization, evolutionary computation, reinforcement learning
"Finland is officially the world’s happiest country. It is also 75 percent forest. I believe these facts are related" - Matt Haig

I started my PhD journey with two goals: to learn more about AI and data science, and to work on timely real-world problems. After a B.Sc. in International Management and a M.Sc. in Business Analytics, I felt the need to complement my business background with more concrete, technical skills. Four years later, and with the help of great colleagues and friends, I am proud to have reached my goal.

My PhD journey at the Aalto University School of Business was everything I envisioned - and so much more. Feelings of self-doubt and “you asked for this!” when attending AI-related courses amid 300 computer science students who all seemed to follow the lecture far easier than me. The joy of getting my first co-authored paper accepted to the prestigious GECCO conference in Cancún, the disappointment when learning it would be hosted remotely due to the COVID outbreak, the excitement of getting nominated for the Best Paper Award, and finally presenting our work live at 4am from the comfort of my home in a neat button-down shirt and sweatpants. The honor of conducting multi-disciplinary research with colleagues from the University of Helsinki, incl. memorable field trips to Finland’s beautiful forests and islands.

None of these experiences would have been possible without the people with whom I’ve been surrounded for the past four years. People like my supervisor Prof. Pekka Malo who trusted from day one that I could master the technical skills for my PhD. Together with Prof. Matti Rossi, my second supervisor, Pekka helped me to become a scientist, and also made me feel welcome in the Finnish society. I will forever cherish our discussions about reinforcement learning, motorcycles, classification algorithms, and heavy weights in the gym.

My gratitude also goes to the co-authors of the papers that form this dissertation (A-Z): Antti Suominen, Dr. Julian Blank, Prof. Kalyanmoy
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My PhD journey got a special twist in November 2020 when my son was born. Joakim, if you read this in a few years, I thank you for ensuring that no work was done outside the core business hours and for taking my mind off work. A tough day at the office was quickly forgotten when being greeted with a big (toothless) smile at home.

To my family, particular my parents and sister, thank you for your love, support, and unwavering belief in me. A special thank you also to my in-laws for child-care support and encouragement.

Finally, I am a truly lucky person for sharing the PhD journey with my amazing wife Hilla. I vividly remember a session during our orientation seminar in 2018 when we were advised not to enter into new relationships during a PhD and, if you were already married, you would be likely to get divorced. Four years later, my wife and I are proud to have proven this statement false. Hilla, who started her PhD on the same day as me but in a different department, supported me throughout the PhD journey, shared the ups and downs, and kept me focused on the goal. This dissertation is yours as well!

Helsinki, August 23, 2022,

Philipp Back
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This thesis consists of an overview and of the following publications which are referred to in the text by their Roman numerals.


Author’s Contribution

**Publication I: “Towards Sustainable Forest Management Strategies with MOEAs”**

Back was the lead author of this article. He contributed to developing the research idea, and he was responsible for the literature review. He also co-authored the discussion of the computational results. Finally, he helped to develop the overall research narrative and presentation.

**Publication II: “Real-World Reinforcement Learning: Observations from Two Successful Cases”**

Back was the sole author.

**Publication III: “Reinforcement Learning in Optimizing Forest Management”**

Back contributed to the development and refinement of the research idea. He also participated in the writing of the paper and in the literature review.
Abbreviations

AI  Artificial Intelligence
CCF  Continuous Cover Forestry
EA  Evolutionary Algorithm
ERL  Evolutionary Reinforcement Learning
ESG  Environmental, Social, and Governance
GDP  Gross Domestic Product
MOEA  Multi-Objective Evolutionary Algorithm
ML  Machine Learning
RF  Rotation Forestry
RL  Reinforcement Learning
SDGs  Sustainability Development Goals
UN  United Nations
1. Introduction

In 2020, the global market for wood products was larger than Sweden’s GDP - over 600 billion USD [57]. However, the way we cultivate and cut this wood is still largely based on rules-of-thumb from the 1900s [41]. This disconnect is even more surprising when considering the value of forests beyond pure timber production, e.g. for CO₂ sequestration and biodiversity preservation. Forests, after all, play a key role in combating climate change and reaching several of the United Nations’ (UN) Sustainability Development Goals (SDGs) [21]. This doctoral thesis thus employs modern optimization methods based on artificial intelligence (AI) to address the century-old question of how to optimally and sustainably manage forest assets, with far reaching implications for forest managers, policy makers, and the environment.

1.1 Background & motivation

Forestry describes the science, business, and craft of purposefully organizing, managing, and utilizing forests and their resources [48]. Forestry can directly and significantly affect the profitability of forest assets, as well as other ecosystem services - including CO₂ sequestration and biodiversity preservation - through forest management operations. The basic unit in forest management is a forest stand, a community of trees that is sufficiently uniform - for example in structure, age, size, class, distribution, spatial arrangement, site quality, or location - to distinguish it from adjacent communities [28, 48]. A forest plan then defines the future forest management operations for each individual forest stand. The boreal and temperate forests of Fennoscandia and North America grow slowly; it can take seedlings over a century to grow to a commercially viable size [58]. Choosing the correct forest management operations and timing them optimally over a long time horizon thus becomes a key challenge for forest stakeholders, such as institutional and private forest owners, forestry consultants, insurance companies, banks, asset managers, ESG
(Environmental, Social, and Corporate Governance) investors, and state authorities. These parties require optimal forest management plans to maximize the utility of their - or their clients’ - forest assets.

A key forest management operation is timber harvesting, which involves the cutting and extracting of trees from a forest stand [32, 23]. In the Nordic countries, two main types of forest management strategies exist: rotation forestry (RF) and continuous cover forestry (CCF).¹

Rotation forestry (Figure 1.1a) has been the dominating strategy across Fennoscandia since the 50’s and follows a clear and repetitive cycle of artificial regeneration, growing, thinning, and final clear-cut harvesting that only leaves a few live retention trees [41]. Economic models for RF build on various extensions of Faustmann’s work from 1849 [27] that optimizes the interval length between clear-cuts to maximize the timber yield. However, studies have shown the adverse ecological effects of clear-cut harvesting [25, 40] that irreversibly destroys natural forest characteristics, ruins habitat diversity, and removes trees as a natural form of carbon sequestration.

Continuous cover forestry (Figure 1.1b) offers a more sustainable alternative that uses selection cutting (thinnings) to harvest individual trees of different sizes and species uniformly from the stand [48]. Harvesting occurs more frequently but less intensely, which not only helps to preserve natural forest characteristics and biodiversity, but also increases carbon sequestration in both trees and soil. Multiple-tree-species CCF thus counters various threats of climate change and is under certain conditions (stand state, species, interest rate, etc.) even more profitable than traditional clear-cutting under single-species RF [5, 35].

![Figure 1.1. Illustration of tree stand development under different forest management regimes. Figure adopted from PI.](image)

¹RF and CCF are often also referred to as even- and uneven aged forestry respectively due to the even/uneven tree age structure that these harvesting regimes produce.
Unfortunately, economic models for CCF become more complex compared to RF as they need to optimize not only the timing of partial harvesting (binary variable; similar to the clear-cut intervals in RF), but also the number of trees harvested per size class and per species (continuous variable).\footnote{Species in the boreal forest typically include spruce, birch, pine, and other broad-leaf trees.} Complications arise from discontinuities, nonconvexities, a large number of decision variables, and a hybrid action space (harvest timings and the choice of harvested tree species are discrete actions; harvested amounts are continuous actions). CCF solutions are thus often only computed under strong simplifications. Existing methods without oversimplifications require days or even weeks to find a single optimal CCF strategy (see e.g. [65, 50]).

What is more, computing CCF strategies efficiently is only part of the challenge. In order to find optimal forest management strategies that maximize forest owners’ long-term goals, it is imperative to have a computational method that can freely choose from the space of all possible solutions, be it clear-cutting or continuous cover management. This makes the problem even more challenging to solve. Without such method, forestry stakeholders often make decisions based on an imperfect understanding of what management strategy is best for a particular objective, which in turn leads to economic losses and unnecessary environmental harm.

Meanwhile, AI research has developed advanced methods for approximating near-optimal solutions for ill-defined dynamic, discrete-time control problems. Reinforcement learning (RL), for example, refers to a machine learning (ML) technique that enables artificial agents to learn near-optimal strategies for sequential decision-making problems by interacting via trial-and-error with a (virtual) environment [63]. Unlike other optimization methods, such as dynamic programming, value iteration, or policy iteration, RL is able to find approximate solutions to problems with vast state and action space - like multiple-species forestry. Furthermore, the multi-dimensional use of forest assets may be explored with multi-objective evolutionary algorithms (MOEAs). Unlike bi-level optimization methods that scalarize the problem a priori, MOEAs allow policy makers to assign preferences for different objectives a posteriori by uncovering the entire Pareto-efficient frontier [19]. MOEAs may thus be used to visualize and negotiate policy trade-offs more efficiently, for example between profit-oriented logging, carbon sequestration, and biodiversity preservation.

However, despite their potential, AI methods such as RL or MOEAs have not been applied to the forestry domain yet. Bridging the two areas presents opportunities to 1) solve long-standing challenges in economic forest research, 2) add forestry as a high-impact application area to AI research, and 3) improve operational practices in forestry - one of the oldest and most mission-critical industries on the planet.
1.2 Research contribution

Against this backdrop, the objective of this doctoral thesis is to uncover novel insights into the optimal and sustainable management of forests by applying AI-based optimization methods that have not been previously used in economic forest research. We emphasize that neither the mathematical formulation of the forestry optimization problem, nor the AI methods are inherently novel. We explicitly build on previous findings in economic forest and AI research. The research contribution of this thesis stems instead from the novel and non-obvious combination of these two domains, and from the resulting insights. The overall research objective is broken down into three sub-objectives that are respectively addressed in the three publications that form this doctoral thesis (see also Figure 1.2):

1. The first objective is to develop a method for balancing conflicting forest management goals by computing and evaluating multi-objective forestry strategies, without the need for policy makers to assign preferences a priori.

2. The second objective is to explore the necessary factors for applying reinforcement learning to real-world business problems; such as optimal forest management.

3. The third objective is to actually apply reinforcement learning for solving high-dimensional optimal harvesting problems that correctly includes stochasticity in forest growth and in the occurrence of natural disasters.

Figure 1.2. Doctoral thesis structure.
With the sub-objectives stated above, this thesis focuses on a deep understanding of the previous work in the field of economic forest research, specifically on optimizing high-dimensional harvesting problems, and in the field of AI-based optimization. The overarching objective of this work is to make methodological contributions, and to uncover novel and practically-applicable insights on optimal and sustainable forest management. More specifically, the articles that form this thesis contribute the first method for simultaneously considering both clear-cutting and continuous cover forest management, and for calculating near-optimal harvesting schedules purely based on the long-term goals of forest owners. Moreover, this work helps to navigate conflict forest management goals, such as economic profit vs. carbon storage vs. biodiversity. Related objectives are designed to prove the methods’ novelty, applicability, efficiency, and robustness.
2. Earlier Research on Optimizing Forest Management

Determining optimal harvest timings and intensities is one of the oldest and still unsolved theoretical problems in forestry. The following section introduces some of the most widely-used approaches. Against this backdrop, the novel methods in Publication I (PI) and Publication III (PIII) are then presented.

2.1 Generic Faustmann rotation model

The infinite horizon model, developed by Faustmann already in 1849 [27], has long served as a cornerstone in both research and practical forestry applications. In its generic form, the model determines optimal forest rotation, i.e. the optimal interval between between two clear-cuts (see Figure 1.1a), and includes income from both thinning and final clear-cuts. Numerous studies have found Faustmann’s [27] approach of calculating forestland value by discounting the net revenues over an infinite horizon to be theoretically correct [49, 60]. Depending on the number of parameters, the optimal timing of thinning intensity can be found analytically [16] or by using dynamic programming [4, 37]. There also exist various extensions of the generic Faustmann [27] model, e.g. to include the possibility of natural disasters [56], stochasticity in forest growth [69], or the value of a standing forest beyond pure timber production (with tree age as a proxy for diversity) [33].

Nevertheless, the Faustmann rotation model [27] remains restrictive as the only optimized parameter is the rotation cycle length, i.e. the interval between two clear-cuts. Moreover, the unit size of the Faustmann [27] model is a whole stand, meaning that forestry operations are always uniformly applied to the entire forest stand. The approach is thus most suitable for classic single-species rotation forestry [70].

Determining mixed-species continuous cover forestry strategies that require optimizing harvest timings and intensities (thinnings) per size class - and not just for the whole stand - is thus difficult using the Faustmann
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[27] formulation. Especially when considering the multi-dimensionality of forests - specifically for combating climate change [6] and halting biodiversity loss [66] - it becomes necessary to move beyond the classic Faustmann model, and to allow for more diverse forest management actions [65].

However, moving from the classic Faustmann model [27], characterized by a chain of exactly similar even-aged cohorts, to a model for more natural forest dynamics with heterogeneous tree structure, expands the dimensionality of the optimization problem significantly [1]. As surveyed by Getz, Wayne, and Haight [30], this curse of dimensionality has lead researchers to develop various assumptions and simplifications. As we will see in the subsequent two chapters, there usually exists a trade-off between utilizing as-realistic-as-possible forest models, and keeping the problem solvable (especially when stochasticity is introduced).

### 2.2 Simplified Markov decision processes

One line of research approaches forest management as a discounted Markov decision process (MPD), \((S,P,D,R,\beta)\), where \(S\) is set of forest states, \(P\) is the probability of transitioning from one state to another, \(D\) is a set of (harvesting) decisions, \(R\) gives the reward for a certain action, and \(\beta\) is the discount factor. The goal is to find an optimal policy \(\pi\) that maps from state space \(S\) to decision space \(D\), i.e. it tells what actions to take given a particular forest stand [71]. In fact, the Faustmann formulation [27] can also be seen as an MDP under deterministic assumptions (unity or zero transition probability) regarding future stand growth and timber prices over an infinite horizon [11].

The discounted MDP formulation corresponds naturally to forest management, where harvesting decisions are made year after year based only on the current forest state. However, MDPs with ecologically realistic forest dynamics quickly become computationally intractable with existing methods due to a large (and possibly continuous) state and action space. For reference, the four-tree-species size-structured problem in PIII has 44 continuous state variables (11 size classes for 4 species), in which each variable can have infinite number of states (the number of trees). The problem is further complicated by a hybrid action space (harvest decisions are discrete, but harvest intensities are continuous).

Many studies thus introduce assumptions on the forest dynamics to simplify the problem - e.g. by limiting the number of forest states or harvesting actions - and to keep it solvable via linear programming. For example, [59] specify a mixed-species size-structured Markov model with stochastic price and stand growth, describing the price by three states and the stand by 64 species or density discrete states, and solve the model by linear programming [20]. Similar model structures and solution methods
are later applied in various extensions [72, 12, 13, 71]. This approach produces decision tables that map each of the 64 discrete stand states and the corresponding optimal transition to a new state depending on stochastic market prices.

On the one hand, simplifying assumptions on the forest dynamics help to keep the problem solvable via linear programming and allow researchers to study the effects of stochasticity on optimal harvesting strategies. On the other hand, this approach sacrifices an as-accurate-as-possible representation of forest dynamics.

### 2.3 Non-linear optimization

Another research stream approaches forest management as an optimization problem. The goal is to formulate a model that is very concrete and accurate in mathematical terms, but also faithful to the ecological models that represent our best possible understanding of how forest behave - without simplifications. The ecological forest models (see e.g. [9, 53, 54, 55]) are taken as given, and the optimization problem is formulated and solved.

However, ecologically realistic forest models without simplifications can currently only be solved using approximate methods that require significant computation time. In [65], for example, Tahvonen et al. apply bilevel optimization [18]: while keeping the harvest timings fixed, the lower-level uses gradient-based interior-point algorithms in AMPL/Knitro [14] to optimize the number of trees harvested per size class and species. The maximized objective value of the lower-level problem is then passed to a genetic algorithm in the upper-level to optimize the harvest timing vector. The Knitro optimizer on the lower-level is called numerous times, which makes this bilevel optimization approach computationally inefficient. Even for single-objective studies, and when simplifying the problem by assuming fully deterministic forest dynamics, the runtime for a full iteration is between 50 - 120 hours [65]. The bilevel optimization approach thus becomes computationally infeasible when (correctly) assuming stochastic forest dynamics, and/or when trying to uncover the Pareto-efficient frontier, i.e. the set of potentially thousands of strategies that represent different yet optimal trade-offs.

In summary, optimizing forest management operations under ecologically realistic assumptions leads to challenging problems that can currently only be solved under strong simplifications, or by using approximate methods that require significant time to converge. Although the bilevel optimization approach in [65] (eventually) produces near-optimal solutions, the long runtime prevents this method to be used for practical forest management.
The main research methods of this thesis are mathematical modeling and optimization. In the following, we formalize the forest management problem using a size-class structured transition matrix model. This generic formulation is then extended in PI to express multiple objectives, and in PIII to include stochasticity. Following the problem formulation, this section also provides a brief overview of the methods that are used to solve the respective model formulations: (Multi-objective) evolutionary algorithms (PI) and reinforcement learning (PIII).

3.1 Ecological model

The dissertation articles PI and PIII utilize a size size-structured forest growth model [54] which has been estimated from empirical Finnish forest data. The model is widely used in economic forest research (see e.g. [5, 64, 65]), and includes functions for ingrowth, natural mortality, and diameter increment in mixed-species stands. Given the scope of this thesis, we focus on the functions that are essential for understanding the generic problem formulation, and refrain from describing all functions, e.g. for ingrowth \( \phi \), stand growth \( \alpha \), and natural mortality \( \mu \) in detail. Their exact formulation lays within the domain of forestry research and is thus beyond the scope of this thesis on AI for forestry optimization. For more information, we kindly refer the interested reader to Appendix A of PIII that contains detailed formulas and the numerical parameter values.

We discretize time into intervals of \( \Delta \) years (5 years in PI and PIII) and denote these time steps by \( t = t_0, t_0 + 1, ..., T \), where \( T \) is the rotation length between clear-cuts, and \( t_0 \) is the time needed for artificial regeneration of trees after a clear-cut (the size-structured forest growth model [54] does not describe well the growth and forestry operations between a clear-cut and \( t_0 \)). We let \( r \) denote the interest rate per annum, and \( b^\Delta = 1/(1+r)^\Delta \) the discount factor.

The number of trees (per hectare) of species \( j = 1, ..., l \) in size classes
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$s = 1, \ldots, n$ at the beginning of period $t$ is denoted by $x_{j,s,t}$. Consequently, the state of the entire forest stand at time $t$ can be expressed as a matrix, showing the number of trees in different species and size classes respectively:

$$
\begin{bmatrix}
    x_{11t} & x_{12t} & \ldots & x_{1nt} \\
    x_{21t} & x_{22t} & \ldots & x_{2nt} \\
    \vdots & \vdots & \ddots & \vdots \\
    x_{l1t} & x_{l2t} & \ldots & x_{lnt}
\end{bmatrix}
$$

During each period $t$, the natural growth of trees is formalized as the fraction of trees in species $j$ that move from size class $s$ to the next size class $s + 1$, given by $0 \leq \alpha_{j,s}(x_t) \leq 1$. Similarly, natural mortality during period $t$ - that is trees dying without any human interference - is expressed as $0 \leq \mu_{j,s}(x_t) \leq 1$. Although trees grow continuously, they do not necessarily graduate from one size class to the next each period. Thus, the fraction of trees of species $j$ that remain in the same size class during period $t$ equals $1 - \alpha_{j,s}(x_t) - \mu_{j,s}(x_t) \leq 0$. Finally, natural regeneration - new trees coming up without being planted - of species $j$ is represented by the ingrowth function $\phi_j \geq 0$, with stand state $x_t$ as its argument. Note that including ingrowth is necessary for modeling CCF strategies that rely on natural regeneration.

The use of size-class structured transition matrix models to express forest dynamics is widely established [44]. However, like all models that aim at formalizing complex systems, transition matrix models also have their limitations [51]. One obvious oversimplification is the assumption that trees are evenly distributed within a size class.

3.2 Economical model

With the forest stand state formalized, we can now include harvesting activities, i.e. the felling of trees. The number of harvested trees of species $j$ and size class $s$ at the end of each time period $t$ is given by $h_{j,s,t}$. This formulation assumes that the initial state is bare land, following [64]. The development of the forest stand can therefore be given as

$$
x_{j,1,t+1} = \phi_j(x_t) + [1 - \alpha_{j,1}(x_t) - \mu_{j,1}(x_t)]x_{j,1,t} - h_{j,1,t},
$$

(3.1)

$$
x_{j,s+1,t+1} = \alpha_{j,s}(x_t)x_{j,s,t} + [1 - \alpha_{j,s+1}(x_t) - \mu_{j,s+1}(x_t)]x_{j,s+1,t} - h_{j,s+1,t},
$$

(3.2)

where $s = 1, \ldots, n - 1$, $t = t_0, \ldots, T$, and $x_{t_0}$ is a given initial forest state at $t_0$ after a clear-cut and subsequent artificial regeneration.

For the definitions of $\phi$, $\mu$, and $\alpha$ please see Appendix A in PIII. As we cannot harvest more trees than existent in the forest, the harvested
amounts also have to satisfy
\[ 0 \leq h_{j,s,t} \leq x_{j,s,t}. \] (3.3)

Harvesting revenues for thinning (partial harvesting) and clear-cut are given by \( R_{th}(h_t) \) and \( R_{cc}(h_T) \), and the corresponding variable thinning and clear-cut costs are \( C_{th}(h_t) \) and \( C_{cc}(h_T) \), respectively. We also include a fixed harvesting cost \( C_f \) to account for planning and transporting the harvester to the site. The cost from artificial regeneration (i.e. NPV of costs of all operations on the stand after clear-cut but before \( t_0 \)) is donated by \( w \geq 0 \). All revenues and costs are given in \( \mathcal{E}/\text{ha} \). Next, we define binary variables \( \delta_t \) that indicate whether harvesting at a certain period occurs as
\[ \delta_t = \begin{cases} 0, & \text{if } h_{j,s,t} = 0 \text{ for all } s, j, \\ 1, & \text{otherwise.} \end{cases} \] (3.4)

The fixed harvesting costs are thus given by \( \delta_t C_f \). When \( \delta_t = 1 \) a fixed harvesting cost (in \( \mathcal{E}/\text{ha} \)) occurs and the harvesting intensity \( h_{j,s,t} > 0 \) for some species \( j \) and size class \( s \) can be freely optimized. When \( \delta_t = 0 \) both fixed harvesting cost and harvesting amount are zero. The gross profits from thinning (partial harvesting) are then given by
\[ \pi_{th}(h_t) = R_{th}(h_t) - C_{th}(h_t) - \delta_t C_f, \]
and the profits from clear-cut are
\[ \pi_{cc}(h_T) = R_{cc}(h_T) - C_{cc}(h_T) - \delta_T C_f. \]

Detailed formulas for computing the costs \( C_{th} \) and \( C_{cc} \) are given in Appendix A Table A3 in PIII.

### 3.3 Problem formulation

Denoting the bare land value (BLV) by \( J(x_0) \) and the (present value) cost of artificial regeneration by \( w \), we can present the optimization problem for a mixed-species stand as

\[ J(x_0) = \max_{h_t, \delta_t, T \in [t_0, \infty)} \frac{-w + \sum_{t = t_0}^{T-1} \pi_{th}(h_t) b^{\Delta(t+1)} + \pi_{cc}(h_T) b^{\Delta(T+1)}}{1 - b^{\Delta(T+1)}} \] (3.5)

subject to \( x_{j,s,t}, h_{j,s,t} \geq 0 \) for all \( j = 1, \ldots, l \), \( s = 1, \ldots, n \), \( t = t_0, \ldots, T \) and \( x_{j,s,T+1} = 0 \), \( j = 1, \ldots, l \), \( s = 1, \ldots, n \) and Equations (3.1) and (3.2) that represent the development of the mixed-species stand and species interaction arises via the stand density. Equation (3.4) encodes the fact that \( h_{j,s,t} > 0 \) for some \( j \) and \( s \) if and only if \( \delta_t = 1 \).

In this formulation, the optimal choice between RF and CCF is determined by choosing the rotation period \( T \). If the optimal rotation is infinitely
long, the regime is CCF, and if it is finite, the regime is RF. The closest preceding model to this formulation is presented in [31], however, it specifies the details of RF differently from CCF and the time length between thinnings is constant. The specification in equations (3.1) - (3.4) is designed for situations where the only difference between CCF and RF is that the latter includes clear-cutting and artificial regeneration, while the former does not.

In the following two chapters, we briefly introduce the two computational methods that are used in PI and PIII to solve this forest management optimization problem: (multi-objective) evolutionary algorithms and reinforcement learning.

### 3.4 Evolutionary algorithms

An evolutionary algorithm (EA), a subset of evolutionary computation, is a generic population-based metaheuristic optimization algorithm. The metaheuristics are inspired by biological evolution and include reproduction, mutation, recombination, and selection [67]. Unlike classical optimization methods, EAs usually do not use gradient information, but rather direct search procedures. EAs are often able to find near-optimal solutions to optimization problems with limited computational resources or imperfect information. The general scheme of an EA in pseudocode is given in Algorithm 1:

Algorithm 1 Evolutionary Algorithm Pseudo-Code. Adapted from [24].

1: Initialize population with random candidate solutions
2: Evaluate each candidate
3: while Termination condition is not satisfied do
4:   Select parents
5:   Recombine pairs of parents
6:   Mutate the resulting offspring
7:   Evaluate new candidates
8:   Select individuals for the next generation
9: end while

Evolutionary computation techniques have also been proposed in forest management, especially to study uneven-aged forests under CCF regimes (see e.g. [8]). In [62], the authors let each member of the population represent one harvesting strategy and introduce a customized EA to solve the mixed integer non-linear optimization problem significantly faster than a traditional heuristic branch-and-bound method. The speed-up in computational efficiency then allowed novel insights into the optimal management of uneven-aged forests. The single-tree EA approach in [62]
was later extended in various studies, e.g. by [65] to include multiple tree species and stand diversity.

EAs are also widely used for multi-objective optimization, an area of multiple criteria decision making that involves optimizing several objectives simultaneously [19]. This task becomes challenging when the objectives are conflicting so that no single solution exists that simultaneously optimizes each objective. Optimal forestry policies, for example, must balance profit-oriented logging with ecological and societal interests.

Solving such problems will lead to trade-off (near-) optimal solutions - also known as Pareto-optimal, Pareto-efficient, or nondominated solutions - where none of the objective values can be improved without degrading some of the other objective values. Without additional information on the subjective preferences of a decision maker, there may exist a possible infinite number of Pareto-efficient solutions, all of which are considered equally good [19]. Multi-objective evolutionary algorithms (MOEAs) are a popular approach to uncover the entire set of nondominated solutions to a multi-objective optimization problem.

Recent publications on optimal forest management stress the importance of additional non-profit objectives - such as carbon sequestration [5] and biodiversity preservation [65] - but usually scalarize the problem a priori by assigning prices to different objectives. The resulting weighted sum can then be solved via single-objective optimization. To the best of our knowledge, PI presents the first application of MOEAs for solving multi-objective optimization problems in economic forest research.

3.5 Reinforcement learning

Reinforcement learning (RL) enables artificial agents to learn near-optimal strategies for sequential decision-making problems. No direct supervision is provided; the agent learns by interacting with a (virtual) environment, and by gathering experience on the quality of its actions in different situations via a reward signal [63]. The interaction between an RL agent and its (virtual) environment is formalized as a Markov decision process (see section 2.2). However, unlike dynamic programming, the exact mathematical form of the MDP does not necessarily need to be known with RL.

RL is one of the three main machine learning paradigms, alongside supervised and unsupervised learning. Modern RL-flavored algorithms have brought astonishing scientific breakthroughs in many domains, such as robotics [38], games [61], economics [15], and bounded rationality [43]. RL-based methods are especially strong in solving stochastic multidimensional optimization problems that have been intractable because of the “curse of dimensionality”. Thus, they naturally correspond to problems of optimal choices in the form of sequential decision-making — a perfect match for
the multidimensional forest management domain, in which harvesting decisions are made year after year based on the current forest state with the aim of maximizing cumulative revenues and/or other objectives.

However, to best of our knowledge, there exists no research prior to PIII on the benefits of tackling the centuries-old problem of optimal forest management [27] under uncertainty with modern RL-flavored methods. Figure 3.1 visualizes RL in the context of forest management. At each discrete time step, the agent observes the current forest state, chooses a harvesting action (either thinning, clear-cutting, or doing nothing; in the case of thinning, the agent also needs to decide the harvest levels as continuous variables), and receives a reward as per-period gross profit. The MDP underlying the environment and agent gives rise to a trajectory of states, forest management actions, and gross profits. The goal of the RL agent is to learn a (near-) optimal strategy - a policy that maps from forest states to harvesting actions - that maximizes the expected cumulative reward.

![Figure 3.1. The agent-environment interaction in the context of forest management. Figure adopted from [63] and PIII.](image-url)
4. Synthesis of the Original Articles

4.1 Article I: Towards Sustainable Forest Management Strategies with MOEAs

Climate change and biodiversity loss demand multi-dimensional forest management that balances profit-oriented logging with ecological and societal interests. Economic forest research, however, has largely focused on profit maximization. Recent publications admittedly stress the importance of additional non-profit objectives, but scalarize the problem a priori by assigning weights to each objective. However, policymakers with diverse objectives may achieve compromises easier if the trade-off between conflicting interests could be quantified and visualized.

In the first article, we therefore formulate a multi-objective forest management problem to maximize profit, carbon storage, and biodiversity simultaneously. The use of MOEAs allows us to assign preferences for different objectives a posteriori by uncovering the entire Pareto-efficient frontier. We analyze the corresponding harvesting schedules in the design space, and further demonstrate how a systematic post-optimality trade-off analysis can be applied to choose a single preferred solution.

We find that the non-dominated set of solutions consists mostly of harvesting strategies with long time horizons, suggesting that continuous-cover forestry is optimal as soon as a balance between profit, carbon storage, and biodiversity is preferred. Clear-cutting and short rotation periods considerably reduce a forest’s biodiversity, while only adding a disproportionately small gain in profit. Sacrificing profit ever so slightly leads to a paradigm shift from RF to CCF.

MOEAs proved highly efficient at solving the underlying complex multi-objective optimization problem, which allowed us to compute and evaluate the entire Pareto front. However, the resulting objective values were 1% - 2% lower compared to the bi-level optimization approach in [65]. When extending the model from 1 to 4 tree species, the EA approach from PI was
likely to lead to even more approximate solutions. Moreover, including stochasticity in the optimization - for example in forest growth and the occurrence of natural disasters - would become cumbersome with the EA approaches that have so far been applied in the forest context. Stochasticity would introduce a moving target for the fitness evaluation, so one would need to run the evaluation repeatedly and compute the average fitness; a computationally inefficient approach.

When the goal is not to uncover the entire Pareto front (consisting of potentially thousands of non-dominated solutions), but to find the single best harvesting strategy for a given forest stand, other optimization methods than MOEAs may therefore be explored.

4.2 Article II: Real-World Reinforcement Learning: Observations from Two Successful Cases

The second article thus marks a methodological change from MOEAs to reinforcement learning. Although RL has achieved superhuman performance in many artificial domains, such as Atari video games or the Chinese board game Go, real-world applications remain rare. RL presents significant challenges that have prevented wide-spread adoption for solving real-world control problems [22].

The second article therefore "tests the waters": we explore what factors drive successful real-world adoption of RL for solving practical (business) problems. By studying "how others did it", we hope to gain a better understanding on whether RL could be a feasible method for forest management. To this end, we explore two successful RL cases: data center cooling at Google and trade order execution at JPMorgan. We perform thematic analysis using a pre-defined coding framework based on the known challenges to real-world RL [22].

First, we find that RL works best when the problem dynamics can be simulated. The learning by trial-and-error framework is hugely sample inefficient, meaning that RL requires a lot of training data to learn (near-) optimal solutions. This explains why most of RL's successes have been with artificial domains: they can usually be simulated which allows for the generation of unlimited training data - an advantage that can hardly be overstated in the context of sample inefficient learning. Google and JPMorgan did not train RL agents directly on historic data, but used said data to build simulation environments. Second, we find that the reward function must capture exactly the desired behavior of an RL agent. Without direct expert guidance, the reward function is the only source of feedback that tells the agent what action in which state was good. Unfortunately, reward function design is notoriously difficult, and the literature presents ample examples of faulty reward functions. Thirdly, safety constraints are
often necessary in the context of trial-and-error learning. This refers to the ability of preventing the agent from exploring undesirable actions.

After exploring the success factors of real-world RL adoption we are confident that forest management is a suitable problem for this optimization technique. The size-structured forest growth models (see e.g. [54]) readily offer empirically-estimated parameters and functions for constructing an ecologically-sound yet mathematically-tractable forest simulation environment. Moreover, the objective functions from PI can be used as a reward function. Only the constraint learning may present an issue, as constraint RL remains a field of active research.

4.3 Article III: Reinforcement Learning in Optimizing Forest Management

The third and final article of this doctoral thesis thus introduces reinforcement learning for optimizing forest management.

As RL has never been used in forestry prior to our work, we first reproduce the current gold-standard solution in [50] to establish trust in our novel method. This means solving a deterministic four-tree-species size-structured problem with continuous state space (the set of all possible forest stand states), and a mixture of continuous (harvest quantities) and discrete actions (timings of clear-cuts and thinnings). We approach the problem of continuous state and action space using the notion of parameterized action space suggested in [26]. We utilize a hybrid proximal policy optimization (H-PPO) algorithm that is based on the broadly applied actor-critic framework, which effectively combines policy (actor) and value-based (critic) methods to solve the RL problem [39]. We find that our RL-based optimization method is able to reproduce the solution in [50], who apply genetic algorithms and nonlinear programming, but only requires approx. 0.06% of the computation time needed earlier.

This dramatic improvement in computation time allows us then to move beyond earlier findings by introducing stochasticity in forest growth and in the occurrence of natural disasters. A stochastic formulation without simplifications is more realistic, but also more complex, and was thus out of reach with earlier methods.

To our surprise, we find only a minor difference in the Net Present Value of the forest between using a deterministic and stochastic formulation for forest growth (certainty equivalent). One explanation is that while stochastic variation is high in natural regeneration (smallest trees), the variation is mild in the larger tree size classes that are actually harvested. However, as supported by earlier studies (see e.g. [17]), adding risk aversion would change this certainty equivalent result and may enhance the optimality of CCF compared to RF.
In contrast to earlier results, we further find that the possibility of natural disasters - such as storm damage, forest fires, insect outbreaks, and droughts - tends to change the optimal management regime from RF to CCF. The effect is similar to an increase in the interest rate which leads to higher discounting of future revenues. As the old saying goes, "a bird in the hand is worth two in the bush": when natural disasters are possible, it is better to be content with what you have (frequent partial harvesting) than to risk losing everything by seeking to get more later (only a final clear-cut at the end of a long period).
In this section the methodological and practical implications of this work on AI-based forestry optimization are discussed.

5.1 Methodological implications

This doctoral thesis establishes forest management as a multi-disciplinary research area by bridging economic forest research with AI research. This offers economic forest researchers new methods for overcoming long-standing challenges, for example how to solve a stochastic high-dimensional optimal harvesting problem without having to simplify the underlying forest dynamics. Especially RL looks promising for being adopted as the new method-of-choice. In the spirit of Open Science, we have thus made our work on RL in optimizing forest management (PIII) freely accessible. We hope that this may help the research community to conduct so far impossible-to-compute experiments that expand our understanding of optimal forest management.

Furthermore, regarding AI research, this thesis introduces forest management as an entirely new application area with great societal relevance for both the MOEAs (PI) as well as the RL (PIII) research community. The methodological contribution is especially remarkable for the latter case, given RL's infamous reputation for being difficult to leverage in the real world [22], PII. We hope that the difficult-to-solve forestry optimization problem will gain in popularity for demonstrating the merits of new algorithmic developments. One could even envision forest management to be added to OpenAI Gym [10], a popular open source toolkit for the development and comparison of RL algorithms. Currently, OpenAI Gym mainly includes environments for teaching artificial agents how to walk, perform robotic tasks, or play Atari video games. Adding a forest environment simulator - similar to the one used in PIII - could help to establish forestry as a standard RL application area, which could in turn increase the amount of research conducted in the field.
5.2 Practical implications

The following section outlines the practical implications of this thesis, specifically related to forestry practices, ESG investments and for reaching several of the UN sustainability development goals.

5.2.1 Forestry practices

In practice, forest management is largely based on best-practice Silvicultural guidelines that offer forest managers rules-of-thumb on how to manage forests “optimally” [48]. These guidelines are deterministic, i.e. they ignore any form of uncertainty or randomness in forest development. They also only offer little support for CCF, compared to extensive RF instructions (see e.g. [3] for Finnish Silvicultural guidelines). Current optimization methods remain applicable only in a lab setting, as they require days or even weeks to find a single (near-) optimal CCF strategy for a forest stand (see e.g. [64, 65]). Institutional forest owners would need to repeat this process every 5 - 10 years for each of their tens of thousands of forest stands; an unreasonable burden. Additionally, forest owners are unable to compare the economic consequences of CCF and RF in order to make a rational choice between these alternatives.

Despite a growing public interest in CCF, there still exists no scientifically-sound and practically feasible tool for forest owners to identify the optimal actions that maximize their long-term goals; including the possibility for both clear-cutting and continuous cover management. Without such method, most forest owners simply stick with the time-tested – but ecologically questionable and often economically suboptimal – clear-cutting and single-tree-species forestry approach for which straightforward but in many sense restrictive models and related commercial software exist.

In contrast, our reinforcement learning optimization method (PIII) converges significantly faster. This drastic improvement in computation time allows us to train our model on multiple initial forest states to learn a global policy. When a forest owner inputs a previously unseen forest state, the model may prescribe the optimal management regime (RF or CCF), the corresponding harvesting schedule, and the forest’s NPV instantaneously; without the need for re-training. Moreover, our approach is the first to combine uncertainty in e.g. timber prices, interest rates, forest growth, and natural disasters with a detailed ecological growth model, which allows us to find more robust strategies. In summary, our research offers forest owners the first scientifically-sound and practically applicable method for finding (near-) optimal forest management strategies, including CCF optimization.
5.2.2 ESG investments

Forests are becoming an increasingly popular ESG/impact investment opportunity. Trees grow steadily regardless of economic turmoil or pandemics, with predictable cash flows that offer investors a natural hedge against inflation and market volatility (see e.g [68, 45, 46]). Unsurprisingly, the market for forestry funds is booming: eight new investment vehicles were launched between 2014 and 2016, and another ten between 2017 and 2019. Globally, 37 impact forestry funds manage USD 9.4 billion in forestry assets, with annual returns ranging from 7% to 18% (8% median) [7].

Forestry investments, however, are only as green as the forest management strategies of the underlying assets. Finland mainly practices Conventional Forestry (Fig. 1.1a) with environmentally harmful clear-cut harvesting. Despite being Europe’s most forested country, Finland’s forests thus remain unattractive for ESG and impact investors who rather seek opportunities in U.S. or Canada.

In PI, we show that environmentally-friendly CCF is oftentimes the superior strategy. This holds especially when the monetary value of the increased carbon offset is taken into account (e.g. via carbon credits). In PIII, we further demonstrate a shift from RF to CCF when uncertainty - specifically in the occurrence of natural disasters - is included in the problem formulation. These results contribute to the ongoing public debate on optimal forest management, and may help to make Finland’s vast forest assets more attractive for ESG investors.

5.2.3 UN sustainability development goals

In 2015, the United Nations adopted the Sustainability Development Goals to end poverty, protect the planet, and ensure worldwide peace and prosperity by 2030 [21]. Forests play a key role in reaching several SDGs, specifically related to Climate Action (Goal 13) and Life on Land (Goal 15).

However, many of the 17 SDGs are integrated, meaning progress in one are will affect outcomes in others. The development must therefore balance social, economic, and environmental sustainability [21]. Our work on multi-objective forestry optimization (PI) offers a tool to balance conflicting interests, e.g. profit-oriented logging vs. biodiversity and CO₂ storage. Most importantly, however, we show that modern AI-based optimization methods can oftentimes find strategies that are simultaneously more sustainable and profitable than current clear-cut practices.

The UN’s report explicitly mentions the importance to improve human, technical, and professional skills for the sustainable use of forests [21]. Our pioneering work on the use of RL for forestry (PIII) is exactly that: a technical leap in optimal forest management.
5.3 Limitations and future research directions

The problem formulation in PI and PIII uses a size-class structured transition matrix model to approximate forest dynamics [44]. The trees of a given forest stand are discretized into 12 size classes. While the matrix model is widely accepted, it oversimplifies forest growth by assuming that tree sizes are evenly distributed within each size class. Certain trees may therefore transition unrealistically fast/slowly between size classes. The matrix model may thus over- or underestimate the growth and related NPV of a forest stand. The economic implications remain open. Future research may adopt a much more detailed individual tree model [47] that specifies the survival and growth of individual trees (or groups of identically sized trees) depending on tree characteristics and tree interaction. While this setup would avoid the aforementioned issues of the matrix model, it would also significantly expand the model dimensions and increase computational costs.

On the computational side, both evolutionary algorithms (PI) and reinforcement learning (PII, PIII) come with inherent advantages and disadvantages. RL typically suffers from the temporal credit assignment problem with sparse rewards (a reward is only observed after a long series of actions) [63], a lack of effective exploration to avoid premature convergence to local optima [52], and brittle convergence properties that are notoriously sensitive to hyperparameters [34]. While sparse rewards are no issue in the PIII setup where the agent observes a reward (period gross profit) after every action, there still remains the challenge of (not) knowing the overall value (discounted cashflows) of a chosen strategy. Meanwhile, EAs are well suited to address each of the RL challenges, but suffer from their own issues. EAs’ inability to leverage powerful gradient-based methods lead to high sample complexity and difficulties in optimizing high-dimensional problems with a large number of parameters [36].

Recently proposed evolutionary reinforcement learning (ERL) may offer the best of both worlds: a multi-objective approach with faster convergence due to intermediate policy updates. ERL leverages the population concept of EAs to generate diversified training data for an RL agent; the RL agent is then periodically reinserted into the EA population to provide gradient information [36]. ERL solves the temporal credit assignment problem with a fitness metric that is invariant to sparse rewards [29], offers effective exploration with a diverse set of policies [42] and the stability of population-based methods [2], while also leveraging gradient information for higher sample efficiency and faster learning. We see evolutionary reinforcement learning also as a promising method for optimizing forest management in future research.
6. Conclusion

This doctoral thesis contributes novel methods and practical insights on optimal and sustainable forest management by applying AI-based optimization methods that have not been previously used in economic forest research.

We address the need to balance conflicting forest management goals via multi-objective evolutionary algorithms (PI), which allows us to compute, evaluate, and visualize multi-dimensional forestry strategies without the need for policy makers to assign preferences upfront. We find that the non-dominated set of solutions consists mostly of harvesting strategies with long time horizons, suggesting that continuous-cover forestry is optimal as soon as a balance between profit, carbon storage, and biodiversity is preferred. The MOEA approach proves highly efficient for uncovering the entire Pareto front, but at the expense of optimality. We therefore decide on a methodological change from MOEAs to reinforcement learning.

To test the waters, we first examine the drivers of successful real-world RL applications (PII). RL's trial-and-error learning is highly sample inefficient, meaning it requires a lot of training data. We find that most successful (ited) historic data, but use it to construct a simulation environment instead. This makes us hopeful for using RL in the forestry context: the size-structured forest growth models (see e.g. [9, 54, 55]) offer empirically-estimated parameters and functions for constructing an ecologically-sound yet mathematically-tractable forest simulator environment.

Finally, we present the first application of reinforcement learning for optimizing forest management in PIII. We demonstrate that RL can repeat earlier solutions in only a fraction of the time, even when considering stochasticity in forest growth and the occurrence of natural disasters. Our proposed RL method is the first to simultaneously consider both clear-cutting and continuous cover forest management, and to calculate optimal harvesting schedules purely based on the long-term goals of forest owners.

In summary, this doctoral thesis makes significant methodological as well as practical contributions. We establish forest management as a multi-
disciplinary research area, by bridging the latest findings in economic forest research with advanced optimization methods from the field of AI research. Moreover, we provide not one, but two new methods - based on MOEAs and RL - for making forestry more profitable and sustainable.


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What is the most productive way to manage forests sustainably? Can AI help forest owners to reconcile conflicting interests such as timber revenues, CO2 sequestration, and biodiversity preservation? This doctoral dissertation contributes novel methods and insights on optimal and sustainable forest management by combining economic, ecology, and AI-based optimization. Our method is the first to simultaneously consider both clear-cutting and continuous cover forest management, and to calculate near-optimal harvesting schedules purely based on the long-term goals of forest owners. Moreover, our work helps to navigate conflicting interests (economic profit vs. carbon storage vs. biodiversity) and establishes forest management as a multi-disciplinary research area by bridging the fields of forest economics and AI. Our results have far-reaching implications for forest owners, policy makers, and for reaching several UN Sustainability Development Goals.