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Original Article

Economic analysis comparing continuous cover forestry and rotation forestry with genetic gain in Norway spruce stands

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Abstract

Growing interest in continuous cover forestry (CCF) has led to an increasing need to compare between CCF and rotation forestry (RF). Here, we introduce the effect of genetic gain into the financial comparison between RF and CCF in Norway spruce (*Picea abies* (L.) Karst.) stands. We applied two datasets: (i) five experimental plots treated with selection cuttings (standing timber *a priori* favouring CCF) and (ii) identical locations and site types corresponding to those five plots, representing bare land cases. A stand-level optimisation framework was applied to maximise net present value for both CCF and RF. The results showed that CCF outperformed RF when the comparison was made from standing timber, regardless of site type (mesic heath or herb-rich) or interest rate (3% or 5%). When starting from bare land, both site type and interest rate played a crucial role: at a 3% interest rate, RF outperformed CCF on both site types—this applied with and without genetic gain associated with RF. At a 5% interest rate, on mesic heath sites, CCF became financially more attractive than RF, both with and without genetic gain. Furthermore, on herb-rich sites, only RF with genetic gain outperformed CCF at the 5% interest rate. Overall, this study has successfully analysed the financial comparison between CCF and RF, incorporating the effect of genetic gain into RF, and provides fundamental insights and valuable information to support economic decision-making in the management of Norway spruce stands.

Keywords: Picea abies (L.) karst.; Motti simulator; bare land value; stumpage price; net present value

Introduction

Most European forests are even-aged, whereas about a quarter are considered to be uneven-aged (Mason et al. 2022). In the Fennoscandian region, rotation forestry (RF), or even-aged management, has been the predominant forestry method (Parkatti et al. 2019), and the use of RF has been justified by the need to ensure and increase material supply flows for forest industries (Kuuluvainen et al. 2012). RF is based on thinnings from below and a clearcut at the end of each rotation, with the next generation of trees being artificially regenerated (Parkatti et al. 2019). However, in some cases, seeding trees and natural regeneration can be applied (e.g. Miettinen et al. 2024). Furthermore, the trees in each rotation are usually more or less even-aged, meaning that the majority of the trees belong to an identical cohort (Sinha et al. 2017). Continuous cover forestry (CCF), on the other hand, primarily relies on selection cuttings and natural regeneration (Parkatti et al. 2019). In CCF, expensive stand establishment costs are avoided since new trees are naturally regenerated by surrounding mature trees, which provide the seeds for the new generation (Danescu et al. 2018). Recent studies on growth and yield of Norway spruce (*P. abies* (L.) Karst.) indicate that tree growth is lower in stands managed according to CCF compared to RF (Hynynen et al. 2019), and there are distinctive differences in growth dynamics between CCF and RF stands (Bianchi et al. 2020). However, CCF has been demonstrated to be financially superior to RF in spruce stands in numerous studies (for a concise summary, see Parkatti 2021).

CCF has been observed to offer various benefits, such as higher resistance to natural hazards like damages caused by insects or wind, better adaptability to climate change (Gauthier et al. 2015), and enhanced environmental, aesthetic, recreational, and cultural values (O'Hara 2014). Moreover, multifunctionality has been demonstrated to be superior in CCF compared to RF (Peura et al. 2018), indicating that CCF may have greater potential to simultaneously produce multiple benefits, including timber net present value.

In the majority of cases, the financial comparison between RF and CCF has been based on numerical optimisation at stand level (e.g. Tahvonen and Rämö 2016, Parkatti et al. 2019, Tahvonen et al. 2022), which enables a transparent and validated calculation

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method grounded in economic theory (Amacher et al. 2009). Another common aspect is that forest growth is estimated by simulating the development of individual trees (e.g. Tahvonen et al. 2022) or tree size classes (e.g. Parkatti et al. 2023). In a widely applied approach, a specific stand-level economic-ecological model is built to solve the optimisation problem numerically (Parkatti and Tahvonen 2020). Furthermore, in the economic-ecological model, a growth model—comprising various sub-models—and an optimisation algorithm are typically integrated into software, with the growth model providing objective function values for the optimisation algorithm (Niinimäki et al. 2012, Ahtikoski and Hökkä 2019). The optimisation task can then be technically addressed as, e.g. a dynamic mixed-integer problem (Tahvonen and Rämö 2016), a hierarchical multi-level problem (Parkatti et al. 2019), or a high-dimensional stochastic problem solved through reinforcement learning (Tahvonen et al. 2022). In general, models for more natural forests (i.e. CCF) contain considerably more heterogeneous trees than RF, which has more uniform even-aged cohorts, making both growth modelling and solving the optimisation problem—due to issues of high dimensionality—a challenging endeavour (Sinha et al. 2017, Tahvonen et al. 2022).

The results of tree breeding are transferred to practice through seed orchards, which are the most common delivery system for genetic gains (White et al. 2007, Haapanen et al. 2016). For instance, in Europe, there are over one thousand seed orchards covering an area of ∼7000 hectares (Paques 2013). Genetic gains encompass, in a broad sense, all genetic and epigenetic effects that cause differences between improved and unimproved forest reproductive material (FRM) (Jansson et al. 2017). There are essentially three approaches to incorporating genetic gains into tree growth models: manipulating the site index (Buford and Burkhart 1987, Xie and Yanchuk 2003), applying genetic gain multipliers (Carson et al. 1999, Gould et al. 2008), or calibrating the model parameters (Sabatia and Burkhart 2013, Deng et al. 2020). In brief, site index manipulation is performed by increasing the dominant height at a given age, i.e. changing the height-age curve equation (Buford and Burkhart 1987), while genetic gain multipliers are based on the relative difference in growth between improved and unimproved natural seed sources (Gould et al. 2008). In general, applying genetic gain multipliers enables extrapolation of progeny test or deployment study results within existing growth models that represent natural, average stands (Gould et al. 2008, Deng et al. 2020).

From an economic perspective, a key question is whether to apply RF or CCF to maximise bare land value (BLV) for existing and newly planted Norway spruce stands. Maximising BLV yields the discounted economic surplus over an infinite horizon (Faustmann 1849)—this applies to both RF (Tahvonen et al. 2013) and CCF (Tahvonen and Rämö 2016). To date, no studies have addressed stand-level optimisation to compare the financial performance of CCF and RF with genetic gains. This study fills this gap by introducing a framework in which genetic gains enhancing Norway spruce tree growth associated with RF are incorporated into the financial comparison between CCF and RF. Technically, genetic gain was modelled within individual tree growth models by applying genetic gain multipliers to the Chapman-Richards type function using a tree-level growth model (for technical details, see Ahtikoski et al. 2012a). Genetic gain estimates were based on growth data from progeny trials involving improved Norway spruce stock in southern Finland (Haapanen 2020). Stand-level optimisation for RF and CCF was conducted starting either from bare land or from an ongoing rotation representing experimental plots explicitly established for studies on uneven-aged Norway spruce forests (see Valkonen et al. 2020, Table 1). In the latter analysis (ongoing rotation), the financial performance of CCF was compared to that of RF without genetic gains; the primary rationale was to test the growth functions applied in this study, and secondarily to perform a ‘reality check’ for optimality when the initial stand structures distinctly favour CCF (Valkonen et al. 2020).

Materials and methods

Data representing standing timber

The study material was derived from five experimental plots (stands) in southern Finland (60°35′–62°40′ N, 25°00′–27°10′ E) at two locations, namely Vesijako and Lapinjärvi (Fig. 1). The stands were established in 1991–1992 (the so-called ERIKA experiments; see Valkonen et al. 2020) and represent two different site types with varying stem numbers, basal area, and growing stock at the onset of the simulations (Table 1). Prior to establishment, all stands were treated with selection cuttings between 1950 and 1980, and from 1984 to 1988, they were managed under a single-tree selection policy (Valkonen et al. 2020). In brief, the stands can be considered to represent stand structures more favourable to CCF than to RF (Lee et al. 2024).

Modified diameter distributions of the plots at the onset are presented in Fig. 2, where diameter classes are divided into five coarse categories and the corresponding proportions are depicted. The categories were chosen to be as informative as possible regarding merchantable wood potential. The classes are as follows: (i) very small trees (diameter classes from 1 to 3 cm, representing midpoints of diameters in 2 cm intervals), (ii) small trees (5–9 cm), (iii) pulpwood (11–19 cm), (iv) saw logs (21–29 cm), and (v) large saw logs (31–44 cm). As a perspective, it takes several decades for very small trees to reach the lower limit of pulpwood dimensions and for small trees to mature into saw logs in southern Finland (see Hynynen et al. 2019, for recent growth and yield results of CCF). Since the ERIKA experimental plots were initially designed with strong potential to develop a sustainable selection structure (Valkonen et al. 2020), it can be expected that the plots were multi-layered from the outset. This is clearly illustrated in Fig. 2: all five plots exhibit a structure of uneven-sized trees. For instance, in plot 4, very small and small trees together accounted for 42%, while saw logs and large saw logs combined accounted for 23%, leaving 35% for pulpwood (Fig. 2).

Data for bare land

When simulations start from bare land, stand characteristics are irrelevant; only location and site type are required. In this study, we used the same locations and site types as those associated with plots 1–5 of standing trees, maintaining the original plot numbering (see Fig. 1 and Table 1).

Models for stand projections in RF

Tree growth was simulated based on stand projections generated by the Motti stand simulator (Salminen et al. 2005, Hynynen et al. 2015). Motti is a stand-level decision-support tool for assessing the effects of forest management on stand dynamics (Salminen et al. 2005, Juutinen et al. 2018, Ahtikoski and Hökkä 2019) and consists of stand-level and individual tree-level distance-independent models. Both the stand-level and individual tree-level models are based on an empirical-statistical modelling approach, utilising a substantial body of long-term inventory

Table 1. Stand characteristics of the experimental plots at the onset of the simulations.

Location	Stand	Site type[a]	N[b] (trees ha^{-1})	Basal area (m^2 ha^{-1})	Volume (m^3 ha^{-1})	Admixture (%)[c]
Vesijako	1	MT	1206	19.9	163	32
Vesijako	2	MT	706	16.7	164	0
Lapinjärvi	3	OMT	1188	14.2	118	50
Lapinjärvi	4	OMT	1181	34.9	371	72
Lapinjärvi	5	OMT	619	19.2	189	62

[a] OMT represents the *Oxalis-Myrtillus* type and MT represents the *Myrtillus* type in the Finnish site type classification system (OMT corresponds to herb-rich and MT to mesic heath; see, e.g. Tonteri et al. 1990 for details). [b] N is the number of stems per hectare. [c] The proportion of broadleaved trees, expressed as a percentage (%).

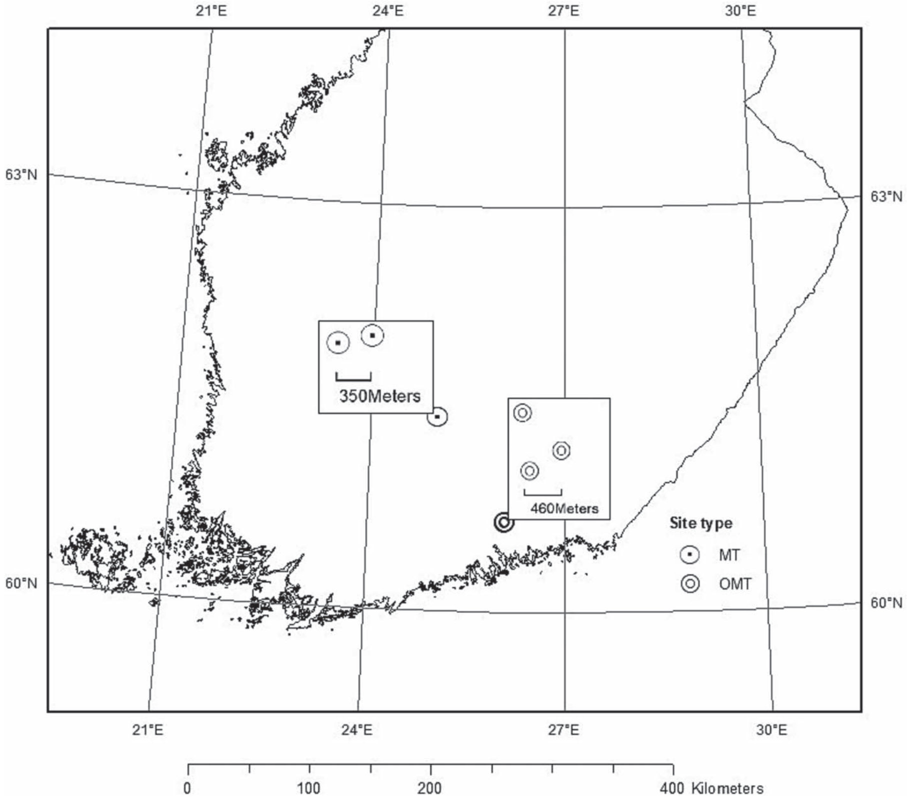

Figure 1. Locations of the experimental plots in southern Finland.

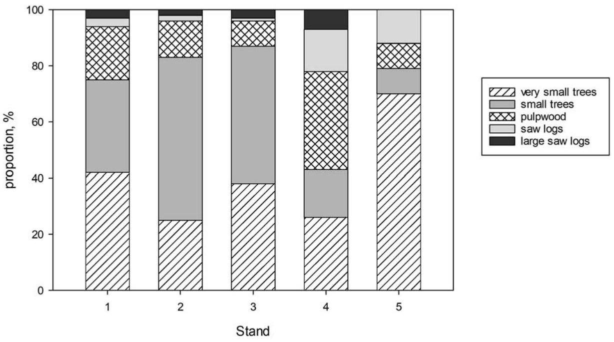

Figure 2. Proportionate diameter distributions according to five categories (very small trees: 1–3 cm, small trees: 4–9 cm, pulpwood: 11–19 cm, saw logs: 21–29 cm, and large saw logs: 31–44 cm) for uneven-aged stands 1–5 at the onset of simulations.

data covering Finland (Matala et al. 2003, Hynynen et al. 2014). Stand-level models are applied for natural regeneration and early growth, while individual tree-level models are used to predict growth for mature trees, where dominant height (Hdom) is greater than ~8 m. In principle, tree growth is predicted using diameter and height growth models, while a crown ratio model is applied to assess thinning response. Furthermore, the competition effect is modelled using stand density to describe both symmetric and asymmetric competition (Hynynen et al. 2002). Mortality and thinning adaptation are also modelled to predict the natural mortality of managed stands and trees' adaptability to new conditions after thinning, respectively. Both diameter and height growth models follow the Richards-type growth function (Richards 1959), which has an asymptotic maximum specific to tree species and soil type (Hynynen et al. 2014).

The growth models are calibrated using the latest National Forest Inventory (NFI) data to reflect growth conditions over time. A thorough description of the models, including mathematical equations and parameter values incorporated into the Motti stand simulator, is presented in detail in the supplementary data. Thus far, the Motti stand simulator has been widely applied both at stand-level (to name a few, Hynynen et al. 2005; Haapanen et al. 2016; Ahtikoski and Hökkä 2019) and in landscape-level analyses (e.g. Mönkkönen et al. 2014, Hynynen et al. 2015, Ahtikoski et al. 2023).

Incorporating genetic gains in RF analyses

With regard to RF and the establishment of stands using improved FRM possessing genetic gain, the following procedure was applied. The development of a stand established with improved FRM was modelled by incorporating genetic gains into height and diameter growth through modification of the asymptote parameter in the Chapman-Richards growth function (see Ahtikoski et al. 2012a, Haapanen et al. 2016). Genetic gain estimates were derived from 15 progeny trials, including 257 seedlots originating from nine wild stands and 17 seed orchards (Haapanen 2020). In this study, a 12.8% genetic gain in height and a 13.5% genetic gain in diameter over unimproved trees were expected from 1.5-generation Norway spruce seed orchards. The results are based on a recent study addressing the performance of genetically improved Norway spruce progeny trials in Finland (Haapanen 2020). After incorporating the genetic gains into the new growth model, the model was integrated into the Motti stand simulator to test its logical behaviour by comparing the simulation results against field measurements (e.g. Deng et al. 2020) and ultimately producing stand projections with genetic gains for the optimisation problem. Additional details of the process for incorporating the genetic gains are further described with equations in the supplementary data.

Models for stand projections in CCF

The stand projection of uneven-aged stands for CCF included: (i) the establishment of new seedlings, (ii) the growth and mortality of seedlings until they reach the threshold size, and (iii) the growth and mortality of advanced trees. Seedling establishment was given using models by Eerikäinen *et al.* (Eerikäinen et al. 2007: Equation 10, Table 3), while the height growth of seedlings was presented by Eerikäinen et al. (Eerikäinen et al. 2014: Equation 1, Table 2) for Norway spruce and by Eerikäinen et al. (Eerikäinen et al. 2007: Equation 18, Table 5) for broadleaves. The establishment process included the initial height distributions for Norway spruce, birch, and aspen (Eerikäinen et al. 2007: p. 453). Increasing basal area restricted both establishment and growth (Eerikäinen et al. 2007, 2014). In the Motti simulator, for each 5-year growth step, we sampled two species-specific percentile trees (h50 and h95, representing the median (50%) and dominant (95%) trees) and followed the development (growth and survival) of these two sampled trees until the threshold value of 6 m median height was reached. Thereafter, the Weibull distribution was recovered from two percentiles (Dubey 1967; Bailey and Dell 1973; Siipilehto 2006), and a systematic sample of n trees per species-specific distribution was taken depending on the number of surviving saplings per hectare (N): $n=1$ if $N<3$, $n=3$ if $4<N<10$, and $n=5$ if $N\geq 10$. The diameter of a tree was determined by the model of Eerikäinen et al. (Eerikäinen et al. 2007: Equations 20 and 21, Table 5) based on tree height. The survival of small seedlings was predicted using height and basal area as driving variables (Eerikäinen et al. 2007: Equations 12 and 14, Table 4). Thereafter, when diameter exceeded 2 cm, models based on tree diameter and basal area of larger trees as driving variables were used (Pukkala et al. 2009: Equation 4, Table 5).

Motti was initially designed for RF, meaning that the individual tree-level growth models were developed and tested mainly using data from even-aged stands (Hynynen et al. 2014). For the growth simulation of uneven-aged stands, the diameter and height growth models of Motti have been tested with empirical CCF data of 20 Norway spruce permanent sample plots monitored over 20–25-years in southern Finland (Lee et al. 2024). Based on the verified biases of tree-level growth predictions, calibration models for diameter and height growth of Norway spruce growing in CCF stands have been developed as functions of variables indicating tree size, tree- and stand-level competition, uneven-aged stand structure, and time after the last selection cutting (Lee et al. 2024). These calibration models were incorporated into Motti to obtain more reliable predictions of tree diameter and height growth in uneven-aged Norway spruce stands. The selected models and parameters are described in Lee et al. (Lee et al. 2024: Equations 1 and (2), Tables 3 and 5). In this study's application, the height calibration model applied was Type 1 from their article, using tree height as the independent variable instead of tree diameter (Lee et al. 2024: Table 5), due to its better accuracy and more conservative predictions when extrapolating. Additional details of the CCF models are further described with equations and parameters in the supplementary data.

Objective function for assessing financial performance

In its simplest form, the problem of maximising net revenues can be given by Eq. 1:

$$\mathbf{Max}\ V(x_0)=\sum_{t=0}^{\infty}(R_t)\,b^t-w \tag{1}$$

$$\{t, R, w\}$$

where x_0 represents the initial stand at time $t=0$; R_t is the revenue valued at stumpage (from thinning or harvest) at time t; w is the discounted silvicultural costs, including regeneration costs and other expenses such as those associated with pre-commercial thinning; and b is the discount factor, defined as $b=1/(1+r)$, where r is the interest rate.

However, since this study compares CCF and RF systems (with RF further including genetic gains), the objective function becomes more complex. First, for RF, the optimisation problem is formulated as a discrete-time system of state and decision variables (e.g. Blot and Naïla 2014). To solve this, the maximum net present value of bare land (also referred to interchangeably as land expectation value), denoted as **Max** LEV_{RF} for timber production in RF, can be expressed by Eq. 2.

$$\text{Max } LEV_{RF}=\frac{\sum_{i=0}^{T} b^{t_i}\left[\sum_{k=1}^{K} p_k h_{ki}\left(Z_{t_i}, g_i, \eta\right)-\sum_{l=1}^{L} wl_{t_i}\right]}{1-b^{t_T}} \tag{2}$$

where Z_{t_i} denote the standing volume ($m^3\ ha^{-1}$) before the i^{th} thinning at age t_i, where $i=0,\ldots,T$ (with t_0 and t_T denoting the beginning and the end of the rotation, respectively); k denotes timber assortments ($k=1,\ldots,K$); and p_k represents the stumpage price (€ m^{-3}) of each timber assortment. Let b be the discount factor, defined as $b=1/(1+r)$, where r is the interest rate in real terms. The cost of a silvicultural measure l is w_l, € ha^{-1} (note that l refers to the last silvicultural measure within a rotation). The removal of each timber assortment k in i^{th} thinning is denoted by h_{ki}, expressed in m^3. Thinning intensity in i^{th} thinning is denoted by g_i, expressed relative to growing stock. The removal is then a function of stand state, thinning intensity, timing, and genetic gain (η), which may be either absent or present. The decision variables include the timings of thinnings, the total number of thinnings, the intensity of each thinning, the timings of silvicultural actions, and the timing of clearcutting (i.e. the rotation period).

Table 2. Stumpage prices (€ m^{-3}) and silvicultural costs (€ ha^{-1}) in real terms. For continuous cover forestry (CCF), stumpage prices were based solely on thinning (comparable to selection cutting in CCF), whereas for rotation forestry (RF), all three stumpage price categories (first thinning, thinning and regeneration felling) were used in the analyses.

Stumpage prices (€ m^{-3})						
Felling method	**Pine logs**[a]	**Spruce logs**	**Birch logs**	**Pine pulp**[b]	**Spruce pulp**	**Birch pulp**
Regeneration felling (RF)	60.49	61.87	46.53	19.41	20.78	18.80
Thinning (RF, CCF)	51.22	52.10	39.52	16.38	16.83	15.76
First thinning (RF)	41.87	43.42	34.95	12.92	12.74	12.63
Silvicultural measures (€ ha^{-1}) used only for RF						
Mounding				411.6		
Manual planting				706.2		
Early pre-commercial thinning				388.0		
Pre-commercial thinning				464.4		

[a] logs for saw logs, [b] pulp for pulpwood

Table 3. Cutting removals (m^3 ha^{-1}), timings (years), and saw log proportions (%) associated with optimal continuous cover forestry (CCF) and rotation forestry (RF) management with 3% and 5% interest rates. Simulations started with standing timber.

		RF		**CCF**	
Stand	**Interest rate**	**Ongoing**	**Future generations**	**Conversion**	**Steady state**
Stand 1	3%	**17**: 263.1 (61%)[a]	**70**: 472.0 (62%)	**40**: 306.8 (66%)	**12**: 81.5 (73%)
	5%	**0**: 150.4 (54%)	**53**: 295.9 (43%)	**50**: 366.9 (64%)	**10**: 58.6 (58%)
Stand 2	3%	**2**: 166.5 (69%)	**57**: 325.2 (42%)	**78**: 514.8 (72%)	**12**: 64.0 (57%)
	5%	**0**: 156.9 (68%)	**53**: 296.0 (43%)	**55**: 365.5 (72%)	**10**: 59.4 (72%)
Stand 3	3%	**0**: 103.4 (58%)	**55**: 492.9 (53%)	**58**: 545.7 (43%)	**13**: 132.2 (62%)
	5%	**0**: 103.4 (58%)	**52**: 453.5 (52%)	**64**: 594.2 (45%)	**11**: 112.2 (62%)
Stand 4	3%	**32**: 568.1 (44%)	**70**: 555.8 (62%)	**74**: 959.0 (54%)	**13**: 136.2 (44%)
	5%	**17**: 474.5 (37%)	**55**: 420.0 (56%)	**62**: 846.5 (56%)	**11**: 110.6 (49%)
Stand 5	3%	**4**: 212.7 (45%)	**70**: 674.4 (67%)	**75**: 681.9 (57%)	**11**: 107.2 (74%)
	5%	**0**: 182.1 (38%)	**53**: 470.9 (51%)	**80**: 711.8 (52%)	**10**: 77.1 (62%)

[a] The entries represent time, volume, and saw log proportions. Bold numbers indicate timing (RF ongoing rotation, CCF conversion) or duration (RF future generations, CCF steady state) in years. The absolute values represent cutting removals (m^3 ha^{-1}), and the percentages show the proportion of saw logs (%). For RF, the absolute values are calculated as the sum of h_{ki} presented in Eq. (2) for ongoing rotations and Eq. (3) for future rotations. For CCF, the absolute values are calculated as the sum of h_{ks} during the transition phase (Eq. (4); second term on the right-hand side), and as the sum of h_{km} in the steady state (Eq. (4); third term on the right-hand side).

Then, the present value to be maximized in RF, denoted as **Max** NPV_{RF} (Eq. 3), with standing timber is calculated by discounting the net revenues from the remaining part of the ongoing rotation and the discounted maximum net present value of bare land (see Hyytiäinen and Tahvonen 2001, for a comparison):

$$\mathbf{Max}\ NPV_{RF} = \sum\nolimits_{i>0}^{T} b^{t_i-n}\left[\sum\nolimits_{k=1}^{K} p_k h_{ki}\left(Z_{t_i-n}, g_i, \eta\right) - \sum\nolimits_{l=1}^{L} w l_{t_i}\right] + b^{t_T-n}\left(\mathbf{Max}\ LEV_{RF}\right) \tag{3}$$

where n is the stand age at the onset of simulations.

With regard to CCF, the net present value to be maximized includes two parts: conversion and steady state (see Tahvonen and Rämö 2016). Regardless of the initial state—either bare land or an existing stand—CCF management starts with a conversion phase (also referred to interchangeably as the transition phase), during which cutting cycles and harvest intensities vary (Rämö and Tahvonen 2017). Gradually, the time between harvests converges towards a steady-state cycle with fixed tree removals in each cycle (Tahvonen and Rämö 2016, Parkatti and Tahvonen 2020). Thus, the net present value to be maximized (**Max** NPV_{CCF}) is given by Eq. 4:

$$\mathbf{Max}\ NPV_{CCF} = \sum\nolimits_{s=0}^{S} b^{t_s} \sum\nolimits_{k=1}^{K} p_k h_{ks}\left(Z_{t_s}, g_s\right) + \frac{p_k h_{km}\left(Z_{t_m}, g_m\right)}{1-b^{t_m}} \times b^{t_S} \tag{4}$$

where t_S is the duration of the transition phase (in years); p_k denotes the stumpage price for timber assortment k (€ m^{-3}), h_{ks} represents the removal of timber assortment k in the s^{th} thinning during the transition phase (m^3 ha^{-1}); Z_{t_s} denotes standing volume during the transition phase; g_s is the thinning intensity in the s^{th} thinning during the transition phase (expressed relative to growing stock), h_{km} is the removal of timber assortment k in the steady state phase, Z_{t_m} represents standing timber at steady state, g_m is the thinning intensity at steady state, which takes t_m years; and b is the discount factor, defined as $b = 1/(1+r)$, where r is the interest rate in real terms. In this study, g_i, g_s, and g_m were set to represent thinning intensities exceeding an absolute value of 30 m^3 ha^{-1}. This was done to avoid repetitive thinnings with removals resulting in unprofitable logging (cf. Laitila et al. 2010, who applied a minimum of 25 m^3 ha^{-1}; see Ahtikoski et al. 2021, for the overall profitability of thinnings under Finnish conditions).

In principle, to maximise the bare land value (Eq. (2)) or the net present value of standing timber (Eqs. 3 and 4) over an infinite time horizon, the optimisation framework seeks the best solution by adjusting decision variables. These include the timing of thinnings, the total number of thinnings, the intensity of each thinning, the timing of silvicultural actions, the timing of clearcutting, and the length of the conversion phase and cutting cycle. Technically, this is achieved by the following procedure. The Motti stand simulator provides the objective function values for the optimisation algorithm (see below, in the section '*Optimisation* *algorithm*') based on the input decision variables. These objective function values result from growth and yield predictions generated by the Motti stand simulator (see Niinimäki et al. 2012, or Arias-Rodil et al. 2015, for a similar procedure). Finally, the optimisation yields the optimal values for the decision variables. Furthermore, these optimal values can be presented using metrics such as the timing of thinnings in years, cutting revenues in euros (primarily expressed as cutting removals by timber assortments, m^3 ha^{-1}), rotation length in years, cutting cycle length in years, and silvicultural costs in euros, including the timing of these costs in years.

Optimisation algorithm

For numerical optimisation, the PIKAIA algorithm (Charbonneau and Knapp 1995, Metcalfe and Charbonneau 2003) was applied, with the objective function being the maximisation of **Max** LEV_{RF}, **Max** NPV_{RF}, or **Max** NPV_{CCF}, corresponding to Eqs. (2), (3), or (4), respectively. The procedure was as follows: the Motti stand simulator produced the objective function values (i.e. stand projections) for the PIKAIA algorithm to solve, in return for decision variables (see Niinimäki et al. 2012, Arias-Rodil et al. 2015). Optimisation was addressed as a mixed-integer nonlinear programming problem (e.g. Sinha et al. 2017). The PIKAIA optimizer belongs to genetic algorithms, which use computer programmes to simulate the evolutionary process by combining an artificial survival of the fittest with genetic operators abstracted from nature (e.g. Holland 1975, Goldberg 1989, Das et al. 2017). In general, genetic algorithms are more effective at finding the global optimum than direct search algorithms. The main advantages of genetic algorithms include their high precision, shorter calculation times (Li et al. 2010), and their ability to avoid local optima (Hadi and Gonzalez-Andujar 2009).

Technically, the PIKAIA algorithm internally seeks to maximise a user-defined function $f(x)$ within a bounded n-dimensional space, where $x \equiv (x_i, x_2, \ldots, x_n)$ and each $x_k \in [0.0, 1.0]$ for all k, by spanning the range $[0.0, 1.0]$ across all dimensions. This restriction to the range $[0.0, 1.0]$ allows for greater flexibility and portability across the problem domain; however, users must adequately normalize the input parameters of the function. The parameter space in this study encompasses a multidimensional and multimodal function, with decision variables for RF such as the timing and intensity of thinning(s) and timing of clearcutting. For CCF, decision variables include the intensity of harvests during both the conversion and steady-state phases, as well as the length of the cutting cycle in the steady state. For optimisation, some default values of the PIKAIA subroutine were adjusted to strike a balance between computing time and result quality. The modified values included the number of generations (100 instead of the default 500) and the population size (50 instead of 100), *ceteris paribus*. During test runs with these two changes, the optimum solution deteriorated by less than 2%, while computing time was reduced by as much as 40–60%. For technical details on the default values of the PIKAIA algorithm and their modifications applied in forestry assessments, see Ahtikoski et al. (2012b) and Juutinen et al. (2018).

The Motti stand simulator, integrated with the PIKAIA algorithm, has been applied in various stand-level analyses in boreal forests (e.g. Ahtikoski et al. 2012b; 2019; 2021). Technically, a specific BAT file was created based on the optimisation data and user selections (e.g. interest rate and minimum cutting removal). The BAT file was then executed to launch multiple executables and link the tasks into sequences that were solved in order. Considerable savings in computing time (up to 80%) were achieved using the above-mentioned procedure, utilising the full capacity of a multi-processor design. On average, computing time varied between 20 and 35 minutes for RF and between 40 and 55 minutes for CCF for a BAT file to complete one set of optimisation tasks consisting of five stands (1–5), with user-defined interest rate and minimum cutting removal criteria, depending on the silvicultural system involved (either CCF or RF). Finally, the range of thinning intensity for both RF and CCF was set to vary from 4 to 14 m^2 ha^{-1}. This range roughly corresponds to 25 to 105 m^3 ha^{-1} of cutting removal and is realistic for spruce-dominated stands in southern Finland. The specific range was chosen for technical reasons: the software design requires both a lower and upper bound for minimum thinning intensity expressed in m^2 ha^{-1}.

Economic data

Nominal unit costs of silviculture (Natural Resources Institute Finland 2023a: *Silvicultural and Forest Improvement Work*) and stumpage prices (Natural Resources Institute Finland 2023b: *Volumes and Prices in Roundwood Trade*) were obtained from annual statistics covering the most recent 10-year time series. In practice, the time series for both unit costs and stumpage prices covered the calendar years from 2012 to 2021, as unit costs for 2022 were not available at the onset of the simulations (September 2023). The rationale for applying a 10-year time series was to capture multiple business cycles, ensuring that the calculated average included both peaks and troughs. The nominal unit costs and stumpage prices were deflated using the cost-of-living index (Statistics Finland 2023) to convert them into real terms. Silvicultural unit costs and stumpage prices in real terms are presented in Table 2.

Sensitivity analyses

To test the robustness of the results, a sensitivity analysis was conducted on stumpage prices to evaluate how sensitive the outcomes are to changes in key variables. In particular, the main objective was to examine whether the financial dominance between CCF and RF might shift. For this purpose, stumpage prices were adjusted by −20% and +20% simultaneously for both CCF and RF, resulting in three runs: one with the original stumpage price, one with −20%, and one with +20%. Consequently, three simulation runs were performed for each of the five stands. Considering the three cases (CCF, RF without genetic gain, RF with genetic gain), this resulted in a total of 45 separate stand-level optimisation simulations (3 runs × 5 stands × 3 cases). Each optimisation took between 20 and 45 minutes to complete, depending on whether RF or CCF management was applied.

Recent studies (e.g. Rana et al. 2024, Di Fulvio and Lessa 2025) suggest that timber extraction costs (€ m^{-3}) are slightly higher for CCF than for RF, due to factors such as the increased operational complexity associated with CCF. Therefore, an additional sensitivity analysis was conducted. Higher extraction costs correspond to lower stumpage prices, and the following values were adopted for this analysis. In Rana et al. (2024: Supplementary data, Table S3), differing timber extraction costs for RF and CCF were deducted from log wood prices, resulting in a stumpage price for CCF that was ∼18% lower than for RF. This figure is consistent with the range reported by Di Fulvio and Lessa (2025). Accordingly, an 18% lower stumpage price level for CCF compared to RF was applied (see Table 2 for the original stumpage prices by cell). For simplicity, this sensitivity analysis was performed only for the locations of Stand 1 and Stand 5, using a 5% interest rate and starting from bare land. Additional information on the sensitivity analyses is provided in the supplementary data.

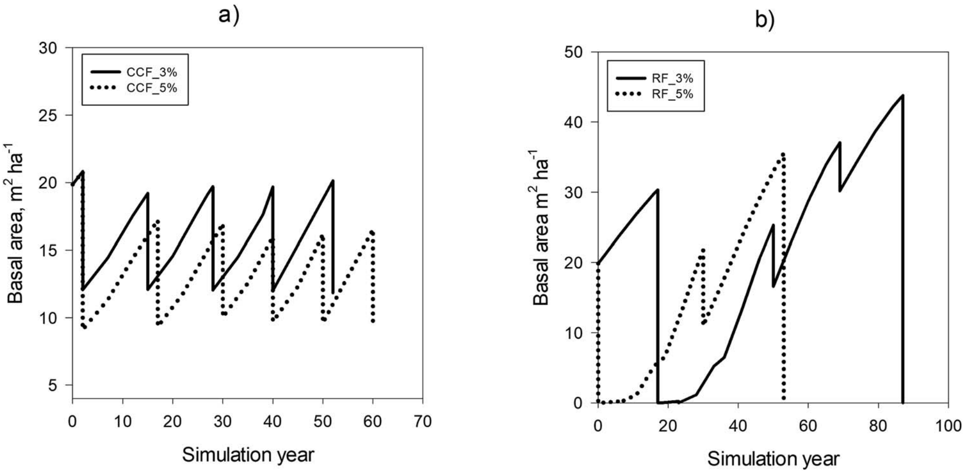

Figure 3. Basal area (m^2 ha^{-1}) under optimal CCF (a) and RF (b) for Stand 1. Solid lines represent optimal management with a 3% interest rate, while dotted lines represent optimal management with a 5% interest rate. For illustrative purposes, CCF lines are truncated after the first steady-state cutting cycle (a), and RF lines are truncated after the first full rotation (b).

Results

Growth and yield starting with standing timber

When starting with standing timber, the optimal CCF system converged to a steady state relatively quickly (Fig. 3, Table 3). For instance, in Stand 1, it took either 40 or 50 years to reach this steady state, depending on the interest rate applied (Fig. 3a, Table 3). Regarding RF, there was a considerable difference between the optimal solutions at interest rates of 3% and 5%, particularly concerning the timing of the clearcut during the ongoing rotation and the rotation length of future generations (Fig. 3b, Table 3). For the less fertile site type (MT: Stands 1 and 2), the mean annual increment (MAI, m^3 ha^{-1} $year^{-1}$) associated with CCF—including both conversion and steady-state phases—was ~77%–79% of the MAI of RF, which includes ongoing and future generations. In contrast, for the nutrient-rich site type (OMT: Stands 3–5), the corresponding percentage was ~84%–91%, depending on the interest rate (3% or 5%) applied in the optimisation (percentages derived from the values presented in Table 3).

Growth and yield starting from bare land

As expected, the MAI associated with optimal stand management using improved FRM was considerably higher than the MAI without genetic gain in RF (Table 4). Thus, genetic gain had a significant impact on tree growth. In some cases, the optimal rotation length in RF was shortened only slightly when a stand was established with improved FRM, i.e. possessing genetic gain (Fig. 4). When starting from bare land, the optimized time between harvests converges relatively slowly towards a steady-state cycle, ranging between 112 and 134 years (Table 4).

The MAI associated with the steady state of optimal CCF ranged from 78% to 98% of the MAI of optimal RF, depending on the interest rate applied (percentages derived from the values presented in Table 4). As expected, the MAI of cutting removals was lower during the conversion phase than during the steady state (Table 4). For the less fertile site type (Stands 1 and 2), the presence of genetic gain increased the MAI by 13%–19% compared to optimal RF without genetic gain, depending on the interest rate (Table 4). In the nutrient-rich site type, genetic gain increased the MAI by 17%–29% in optimal RF, depending on the interest rate (3% or 5%). Moreover, genetic gain increased the proportion of saw logs in optimal RF compared to RF without genetic gain (Table 4). The steady-state cycle in optimal CCF ranged from 8 to 13 years when simulations started from bare land (Table 4).

Financial performance

With standing timber, CCF outperformed RF, regardless of site type—either mesic heath (MT) or herb-rich (OMT)—and interest rate applied (3% or 5%) (Fig. 5). For instance, on the mesic heath site type (Stands 1 and 2), the average maximum net present value (Max NPV) of RF with a 3% interest rate was ~€8665 ha^{-1}, while the corresponding average for CCF was €9744 ha^{-1} (averages derived from Fig. 5a). With a 5% interest rate on the herb-rich site type (Stands 3–5), the average Max NPV of RF was €6329 ha^{-1} compared to €7703 ha^{-1} for CCF, indicating a greater than 20% difference (averages derived from Fig. 5b). Further details regarding the economic analyses, using Stands 1 and 5 as examples, are described in the supplementary data.

When starting from bare land, RF outperformed CCF at a 3% interest rate, regardless of site type and whether the stand was established with improved FRM or not (Fig. 6a). At a 5% interest rate, there was a clear distinction between site types: on the mesic heath site type (Stands 1 and 2), CCF explicitly outperformed RF, regardless of the presence or absence of genetic gain (Fig. 6b). In contrast, on the herb-rich site type (Stands 3–5), RF with genetic gain resulted in higher Max NPVs than CCF (Fig. 6b). Without genetic gain, RF was inferior to CCF at a 5% interest rate, even on the herb-rich site type (Fig. 6b). At a 5% interest rate on the mesic heath site type (Stands 1 and 2), the average Max NPV of RF was −€233 ha^{-1} without genetic gain and €133 ha^{-1} with genetic gain, while the average Max NPV of CCF was as high as €389 ha^{-1} (Fig. 6b). On the herb-rich site type (Stands 3–5) and at a 5% interest rate, the average Max NPV of RF was €502 ha^{-1} without genetic gain and €1161 ha^{-1} with genetic gain, while the average Max NPV of CCF fell between the two, at €660 ha^{-1} (Fig. 6b).

Sensitivity analyses

The NPVs were sensitive to changes in stumpage prices, as anticipated (Fig. 7). However, the ranking among CCF, RF with genetic gain, and RF without genetic gain remained unchanged across alternative stumpage prices, indicating the robustness of the main results. The largest variation, associated with a −20% or +20% change in stumpage prices, was observed in RF with genetic gain (Fig. 7).

Table 4. Cutting removals (m^3 ha^{-1}), timings (years), and saw log proportions (%) associated with optimal continuous cover forestry (CCF) and rotation forestry (RF) management at interest rates of 3% and 5%. Simulations started from bare land.

		RF		CCF	
Stand	**Interest rate**	**No Gain**[a]	**With Gain**[a]	**Conversion**	**Steady state**
Stand 1	3%	**75**: 518.5 (62%)[b]	**68**: 559.1 (70%)	**134**: 498.3 (36%)	**12**: 76.5 (48%)
	5%	**65**: 423.8 (56%)	**64**: 471.9 (63%)	**113:** 403.8 (34%)	**10**: 60.3 (40%)
Stand 2	3%	**76**: 534.1 (62%)	**68**: 558.9 (69%)	**134**: 496.1 (34%)	**13**: 80.5 (49%)
	5%	**65**: 423.4 (56%)	**65**: 490.3 (65%)	**117**: 421.1 (30%)	**11**: 58.5 (38%)
Stand 3	3%	**65**: 612.6 (64%)	**65**: 762.5 (74%)	**121**: 677.0 (33%)	**10**: 75.2 (51%)
	5%	**56**: 475.1 (56%)	**52**: 548.0 (61%)	**116:** 616.1 (34%)	**8**: 67.3 (45%)
Stand 4	3%	**65**: 616.2 (63%)	**65**: 762.3 (72%)	**123**: 659.3 (37%)	**10**: 74.3 (51%)
	5%	**56**: 479.0 (56%)	**57**: 629.8 (63%)	**113:** 621.0 (34%)	**9**: 70.0 (47%)
Stand 5	3%	**65**: 609.3 (64%)	**65**: 759.2 (72%)	**120**: 656.8 (32%)	**10**: 73.1 (47%)
	5%	**56**: 486.9 (56%)	**50**: 510.3 (59%)	**112**: 476.6 (27%)	**8**: 68.9 (46%)

[a] No Gain refers to tree growth without genetic gain, while With Gain shows values when a RF stand is established with improved forest reproductive material (FRM). [b] The entries represent time, volume, and saw log proportions. Bold numbers for RF indicate rotation length in years, while for CCF they indicate the duration of the conversion phase and steady state in years. The absolute values represent cutting removals (m^3 ha^{-1}), and the percentages show the proportion of saw logs (%). For RF, the absolute values are calculated as the sum of h_{ki} presented in Eq. (3), starting from bare land. For CCF, the absolute values are calculated as the sum of h_{ks} during the conversion phase (see Eq. (4)), and as the sum of h_{km} in the steady state (Eq. (4)).

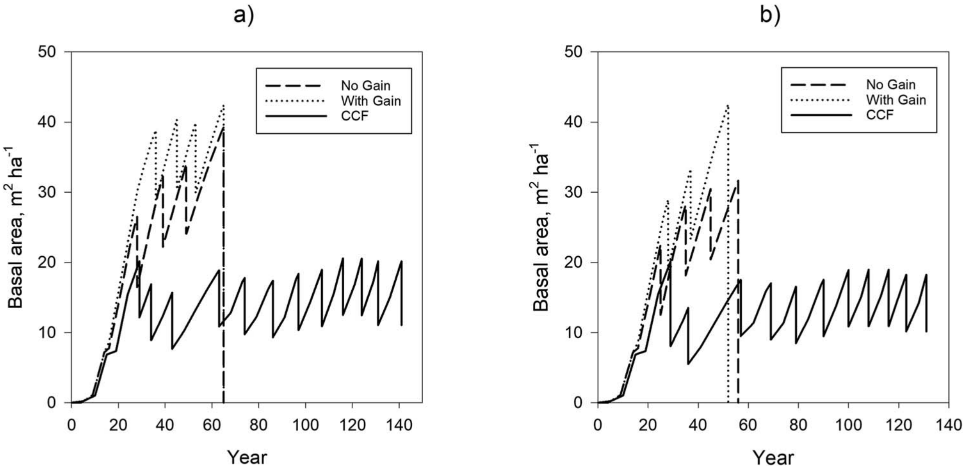

Figure 4. Basal area (m^2 ha^{-1}) under optimal CCF and RF, with genetic gain (With Gain) and without genetic gain (No Gain) applied only to RF, when starting from bare land in Stand 3, with an interest rate of 3% (a) or 5% (b).

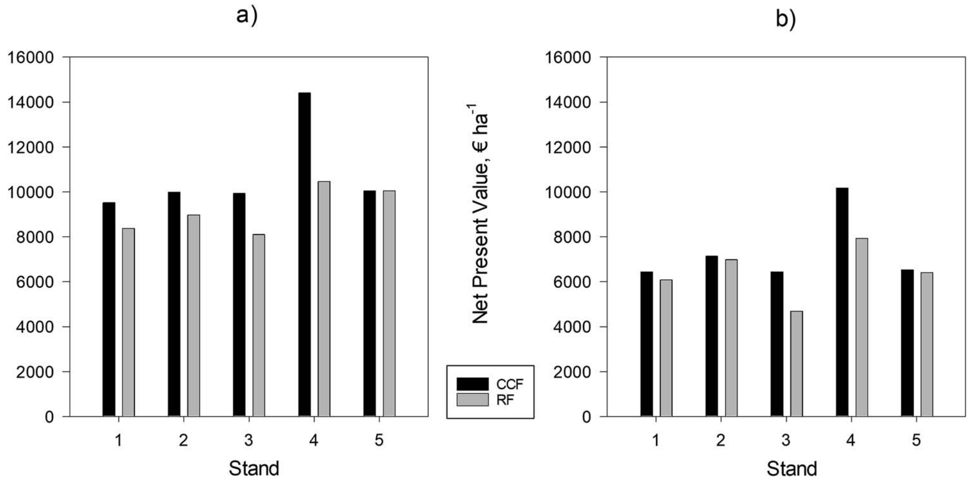

Figure 5. Maximum net present values (max NPVs, € ha^{-1}) associated with CCF and RF at interest rates of 3% (a) and 5% (b). Results are shown for each Stand (1–5) starting with standing timber. Stands 1 and 2 represent mesic heath site types (MT), while Stands 3, 4, and 5 represent herb-rich site types (OMT).

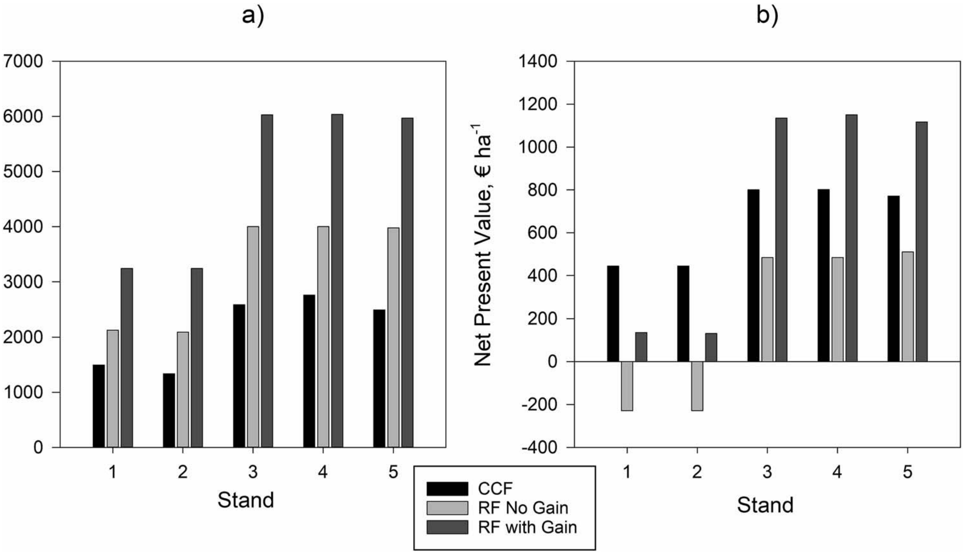

Figure 6. Maximum net present values (max NPVs, € ha^{-1}) associated with CCF and RF at interest rates of 3% (a) and 5% (b). Results are shown for each Stand (1–5) starting from bare land. RF with Gain indicates RF with genetic gain, i.e. RF established with improved forest FRM, while RF No Gain shows max NPV without genetic gain. Stand numbering corresponds to that in Fig. 5.

Table 5. Sensitivity analysis with an 18% lower stumpage price for CCF compared to RF. Values are expressed in € per hectare, assuming a 5% interest rate.

Stand	CCF*	CCF lower stumpage prices	RF No Gain*	RF with Gain*
Stand 1	444.0	344.4	−228.7	135.8
Stand 5	771.2	593.8	520.2	1116.2

*The bars in Fig. 6b represent identical values for Stand 1 and Stand 5.

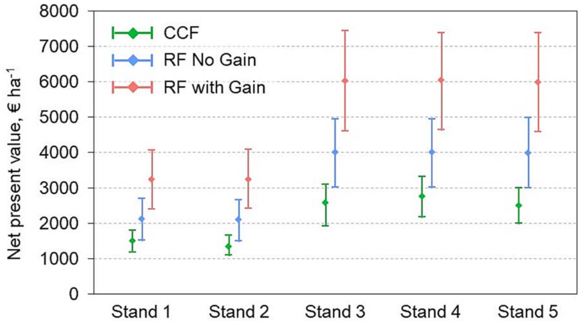

Figure 7. Sensitivity of net present values (NPVs) to stumpage prices within a −20% to +20% range, with an interest rate of 3%. The cross lines within the bars represent NPVs calculated using the original stumpage prices (identical to the bar heights shown in Fig. 6a), while the lower ends of the bars indicate NPVs with a −20% stumpage price and the upper ends indicate NPVs with a +20% stumpage price, *ceteris paribus*. CCF denotes continuous cover forestry; RF No gain denotes rotation forestry without genetic gain; RF with gain denotes rotation forestry with genetic gain.

When stumpage prices were adjusted downward only for CCF, the original ranking between RF and CCF was unchanged (Table 5). For example, at Stand 5 (herb-rich site type), reduced stumpage prices for CCF decreased its bare land value relative to the original value but did not alter the ranking: RF with Gain remained the best performer while RF No Gain was the worst. At Stand 1 (mesic heath site type), CCF remained the best performer even with the lowered stumpage prices (Table 5). Further details regarding the sensitivity analyses, using Stands 1 and 5 as examples, are described in the supplementary data.

Discussion

Theoretical framework for financial comparison of CCF and RF

To compare the financial performance of CCF and RF in a theoretically sound manner, certain prerequisites must be met. First, with a positive interest rate (>0%), the steady state must be solved simultaneously with the transition path; it is not possible to find the optimal steady state independently of the optimal path leading to that steady state in CCF (Tahvonen and Rämö 2016). Second, the comparison between CCF and RF must be solvable from any initial state (Sinha et al. 2017). Since the curse of dimensionality is generally present in forest management optimisation problems, these two conditions become particularly challenging to satisfy (Parkatti et al. 2019, Tahvonen et al. 2022). From a practical point of view, the outcomes (i.e. optimal solutions) associated with CCF and RF must be plausible; this translates to credibility: the outcomes should be achievable from a management perspective for each participating agent, particularly private forest owners. This study compared CCF and RF in terms of financial performance (Max NPV), starting from two initial states (standing timber and bare land) across five individual stands, assuming that improved FRM could be used in RF. To our knowledge, this is the first attempt to incorporate the effect of genetic gain into the profitability comparison between RF and CCF (cf. Tahvonen et al. 2010, Tahvonen and Rämö 2016, Parkatti et al. 2023).

Financial performance of CCF and RF starting from standing timber

When starting with standing timber (i.e. an ongoing rotation with growing trees), the results indicated that CCF outperforms RF in all five stands across both interest rates applied. This finding aligns with existing literature focusing on spruce stands on mineral soils (Tahvonen et al. 2010) and peatlands (Juutinen et al. 2021). However, the conversion phase (transition harvests) under optimal CCF solutions in our study tended to take slightly longer than those presented in Rämö and Tahvonen (2017). On the other hand, this aligns well with a recent paper (Tahvonen et al. 2022) demonstrating that the conversion to steady state in optimal CCF takes more time with individual-tree models (which relate to the present study) compared to size-structured matrix models (Rämö and Tahvonen 2017). Additionally, the financial superiority of CCF over RF is distinctly evident here. One explanation for this is that the initial stands (Table 1) had undergone selection to be representative of uneven-aged structured forests (Valkonen et al. 2020). Thus, the results of this study appear to confirm this observation. Another reason for the financial superiority of CCF over RF when starting with standing timber is the time value of money (Gitman and Zutter 2015). In other words, earlier cutting revenues in CCF compared to RF result in a higher present value due to the discounting effect. Additionally, CCF does not involve establishment costs, which further enhances its profitability.

Besides the effect of site type (mesic heath or herb-rich), other factors such as diameter distribution and stocking also influenced financial performance. For example, Stand 4 had the widest diameter distribution and the largest stocking among the stands (Table 1 and Fig. 2), which contributed to its being the best financial performer under CCF (Fig. 5). This underscores the importance of careful stand selection for CCF. Finally, there is no need to compare absolute values of Max NPV between this study and others, as discrepancies in initial stand characteristics exist across studies (for instance, compare Table 1 and Fig. 2 of this study with those in Tahvonen et al. 2010, and Rämö and Tahvonen 2017). Such discrepancies are likely to result in different financial outcomes in absolute terms.

Financial performance of CCF and RF starting from bare land

The results of this study became particularly intriguing when the analyses began from bare land. At a 3% interest rate, our findings clearly contradicted earlier results with spruce (Tahvonen 2016; Tahvonen and Rämö 2016; Parkatti et al. 2019). Those earlier studies demonstrated that at a 3% interest rate or higher, CCF clearly outperformed RF, whereas the results of this study indicated the opposite. Thus, the underlying rationale for this difference requires an in-depth examination of the prerequisites and assumptions applied. First, earlier studies (Tahvonen, 2016; Tahvonen and Rämö 2016; Parkatti et al. 2019) used site indices initially developed for Norway to describe the potential for tree growth (Bollandsås et al. 2008). However, these indices can be converted into the Finnish system by adjusting reference age for dominant height, using growth and yield tables provided by Vuokila and Väliaho (1980); see Rämö and Tahvonen (2014) for details. Nevertheless, those site types appear to have lower fertility and, consequently, a reduced potential for tree growth compared to the site types applied in this study. This is evident when comparing the average annual yields associated with the optimal solutions of CCF: in Tahvonen and Rämö (2016), the annual average yield ranged between 3.1 and 6.1 m^3 ha^{-1} at a 3% interest rate, while in Parkatti et al. (2019), the average annual yield under maximum sustainable yield (MSY) varied from 2.4 to 7.3 m^3 ha^{-1}. Note that in Tahvonen (2016) and Parkatti et al. (2019), average annual yields for financially optimal solutions were not reported. In this study, the annual average yield under optimal solutions at a 3% interest rate in steady state varied between 5.3 and 8.8 m^3 ha^{-1}, depending on the site type (either mesic heath or herb-rich). Furthermore, in a recent study (Parkatti et al. 2023), the annual average yield associated with the optimum solution (excluding soil carbon) was 4.1 m^3 ha^{-1} at a 3% interest rate.

Since tree growth positively correlates with potential financial profitability (e.g. Cubbage et al. 2009), it is useful to compare the absolute values of NPV reported in earlier studies with those obtained in this study. At a 3% interest rate, the average Max NPV for CCF on the mesic heath site type was €1321 ha^{-1}, while on the herb-rich site type, the corresponding value was €2107 ha^{-1}. In Parkatti et al. (2019), the bare land value of optimized CCF ranged from €127 ha^{-1} to €822 ha^{-1}, depending on the growth model applied (Pukkala or Bollandsås) and the cost of artificial regeneration (either €1500 ha^{-1} or €2000 ha^{-1}). The bare land value associated with optimized CCF, excluding soil carbon pricing, was €1985 ha^{-1} at a 3% interest rate according to Parkatti et al. (2023) for the Myrtillus type (i.e. mesic heath) spruce stand; this value is comparable to those found in this study. Another similarity between this study and earlier research is the duration of the conversion phase; here, it took between 112 and 134 years to achieve a steady state at a 3% interest rate. Earlier studies have reported similar time spans for the conversion phase when CCF is optimized at a 3% interest rate starting from bare land (Parkatti et al. 2019, Tahvonen et al. 2022).

Impact of genetic gain on financial performance

At a 5% interest rate, the results revealed a clear division between site types. For instance, on the mesic heat site type, CCF was financially superior to RF. However, on the herb-rich site type, CCF was overshadowed by the effect of genetic gain; RF with improved RFM resulted in better profitability than CCF. Conversely, without any genetic gain, CCF outperforms RF (Fig. 6). The rationale for this is that, with boosted tree growth due to the use of improved FRM, the high costs associated with artificial regeneration in RF (see Table 2) are well compensated by the higher present value of revenues from thinnings and clearcuts, compared to those of unimproved FRM. It is noteworthy that the costs of artificial regeneration in RF remain identical regardless of genetic gain, which is attributable to nursery technology. This result—where RF with improved FRM outperforms CCF at a 5% interest rate—offers original perspectives for comparing forest management strategies, although further study is still required. The inclusion of genetic gain in the financial comparison between RF and CCF adds a new aspect to the discussion.

Key methodological factors impacting financial comparisons between CCF and RF

In the optimisations, interest rates of 3% and 5% were applied in both cases (starting from standing timber or from bare land); possible differences in the results would be easier to interpret if identical interest rates had been used. The applied interest rates (3% and 5%) fall within the range commonly employed in such analyses (e.g. Tahvonen and Rämö 2016, Parkatti 2021). In general, the longer the time horizon, the lower the interest rate applied (Weitzman 2010). It has been suggested that interest rates around 2% to 6% may be relevant for a large fraction of forest owners in the boreal zone (Hyytiäinen and Tahvonen 2001). Finally, there are three distinct aspects affecting the results. First, in this study, the Motti stand simulator was used to generate stand projections. The Motti stand simulator produces projections based on individual-based statistical-empirical models, whereas the majority of existing literature comparing the financial aspects of CCF and RF typically employs size-structured matrix models (e.g. Rämö and Tahvonen 2017, Parkatti et al. 2019, Parkatti et al. 2023). The use of different stand growth models undoubtedly has an impact on the final results as well (see, e.g. Parkatti et al. 2019; Österberg et al. 2023; Tahvonen et al. 2024). Closely related to the stand growth model is the average sawlog yield (sawlog proportion or sawlog ratio), which depends on both the applied stand growth model and the taper curve. Notably, in this study (Tables 3 and 4), the sawlog proportions associated with optimal CCF solutions were considerably smaller than those reported in the existing literature (cf. Parkatti et al. 2019, Österberg et al. 2023). This discrepancy, of course, affects the financial comparisons.

Second, in this study, stumpage prices were used, whereas in the existing literature, harvesting costs are usually included in the analyses (see, e.g. Tahvonen and Rämö 2016; Parkatti et al. 2019). This difference is significant because, when harvesting costs are included (i.e. they are endogenous) in the analyses, the optimisation process selects only thinnings that generate positive revenues, meaning that cutting revenues exceed harvesting costs. On the other hand, in this study, the use of stumpage prices might have resulted in frequently repeated thinnings with potentially very small cutting removals (since there were no costs associated with thinnings) if we had not implemented a specific procedure. In other words, repetitive minuscule cutting removals were prevented exogenously by setting a minimum cutting removal of 30 m^3 ha^{-1}. Nevertheless, the distinction between endogenous and exogenous settings remains, which could make a difference. The reason harvesting costs were not included in the analyses of this study relates to a recent paper (Bianchi et al. 2023) indicating that harvesting cost models applied in the existing literature on financial comparisons between CCF and RF behave differently at various stages of CCF. In other words, they either underestimate or overestimate actual costs depending on the development stage of CCF, whether in conversion or steady state (Bianchi et al. 2023). In this study, officially reported actual stumpage prices were applied to avoid such biases.

Third, the optimisation algorithms applied in the existing literature differ from the optimisation framework used in this study. Here, a genetic algorithm known as PIKAIA was employed (Metcalfe and Charbonneau 2003; Juutinen et al. 2018, Supplementary data). In the existing literature, the approach has been slightly different: the optimisation task is usually solved as a multilevel optimisation problem by applying genetic, hill-climbing, and gradient-based algorithms at different levels (e.g. Tahvonen and Rämö 2016; Parkatti et al. 2019). In recent papers (Tahvonen et al. 2022, Tahvonen et al. 2024), reinforcement learning (RL) has been applied to solve optimisation problems. However, there are only a few studies that compare of different optimisation algorithms used in stand-level optimisation (e.g. Pukkala 2009, Arias-Rodil et al. 2015). This is due to the considerable work effort required for such comparisons, as it would necessitate incorporating alternative optimisation algorithms into an identical tree growth simulator, which would be immensely time-consuming. Therefore, the effect of the chosen optimisation algorithm on optimal solutions requires further study.

Finally, one can argue that incorporating genetic gain into the financial comparison between RF and CCF significantly altered the outcome. For example, when starting from bare land on herb-rich site types, RF with genetic gain distinctly outperformed CCF, whereas RF without genetic gain was inferior to CCF, assuming an interest rate of 5%. Furthermore, at a lower interest rate of 3%, RF with genetic gain was clearly the best financial performer regardless of site type, whether herb-rich or mesic heath. However, these results apply only to southern Finland, highlighting the need for further studies that also cover northern Fennoscandia.

Conclusion

The results of this study demonstrated that the economic superiority of either RF or CCF for managing Norway spruce stands in Finland depended on various conditions and assumptions. For instance, site type and interest rates were both relevant factors: starting from bare land with lower nutrient status (mesic heath versus herb-rich) and a higher interest rate (5% vs. 3%), CCF financially outperformed RF, regardless of whether improved FRM was applied in RF or not. However, with the same interest rate (5%) on herb-rich soil, RF with improved FRM outperformed CCF. Furthermore, when stand structures were favourable to CCF (e.g. multilayer cohorts of trees with a sufficient number of saplings), CCF outperformed RF at both interest rates (3% and 5%), regardless of whether improved FRM was applied. We concluded that the financial comparison between CCF and RF is more complex than existing literature has suggested; therefore, further studies are called for.

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Author contributions

Daesung Lee (Conceptualization, Data curation, Methodology, Writing—original draft, Writing—review & editing), Anssi Ahtikoski (Conceptualization, Investigation, Methodology, Writing—original draft), Jouni Siipilehto (Conceptualization, Data curation, Writing—review & editing), Jaakko Repola (Data curation, Formal analysis, Writing—review & editing), Katri Karkkainen (Conceptualization, Methodology, Writing—review & editing), Mika Lehtonen (Formal analysis, Investigation, Methodology, Writing—review & editing), and Jari Hynynen (Conceptualization, Validation, Writing—review & editing)

Supplementary data

Supplementary data are available at *Forestry* online.

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Data availability

The data underlying this article will be shared upon reasonable request to the corresponding author (daesung.lee@luke.fi) or co-author (anssi.ahtikoski@luke.fi).

References

Ahtikoski A, Hökkä H. Intensive forest management – Does it financially pay off on drained peatlands? *Can J For Res* 2019;**49**:1101–13. https://doi.org/10.1139/cjfr-2019-0007.

Ahtikoski A, Laitila J, Hilli A. *et al.* Profitability of the first commercial thinning, a simulation study in northern Finland. *Forests* 2021;**12**:1389. https://doi.org/10.3390/f12101389.

Ahtikoski A, Nikula A, Nivala V. *et al.* Cost-efficient forest management for safeguarding Siberian flying squirrel (*Pteromys volans*) habitats in Central Finland. *Scand J For Res* 2023;**38**:197–207. https://doi.org/10.1080/02827581.2023.2208875.

Ahtikoski A, Ojansuu R, Haapanen M. *et al.* Financial performance of using genetically improved regeneration material of scots pine (*Pinus sylvestris* L.) in Finland. *New For* 2012a;**43**:335–48. https://doi.org/10.1007/s11056-011-9284-6.

Ahtikoski A, Salminen H, Hökkä H. *et al.* Optimising stand management on peatlands: The case of northern Finland. *Can J For Res* 2012b;**42**:247–59. https://doi.org/10.1139/x11-174.

Amacher GS, Ollikainen M, Koskela E. *Economics of Forest Resources*. Cambridge: The MIT Press, 2009, 448.

Arias-Rodil M, Pukkala T, Gonzalez-Conzalez JM. *et al.* Use of depth-first search and direct search methods to optimize even-aged stand management: A case study involving maritime pine in Asturias (Northwest Spain). *Can J For Res* 2015;**45**:1269–79. https://doi.org/10.1139/cjfr-2015-0044.

Bailey RL, Dell TR. Quantifying diameter distributions with the Weibull function. *For Sci* 1973;**19**:97–104.

Bianchi S, Ahtikoski A, Muhonen T. *et al.* Evaluation of operating cost management models for selection cutting in Scandinavian continuous cover forestry. *iForest.* 2023;**16**:218–25. https://doi.org/10.3832/ifor4204-016.

Bianchi S, Huuskonen S, Siipilehto J. *et al.* Differences in tree growth of Norway spruce under rotation forestry and continuous cover forestry. *For Ecol Manage* 2020;**458**:117689. https://doi.org/10.1016/j.foreco.2019.117689.

Blot J, Naïla H. *Infinite-Horizon Optimal Control in the Discrete Time Framework*. New York: Springer, 2014, 126.

Bollandsås OM, Buongiorno J, Gobakken T. Predicting the growth of stands of trees of mixed species and size: A matrix model for Norway. *Scand J For Res* 2008;**23**:167–78. https://doi.org/10.1080/02827580801995315.

Buford MA, Burkhart HE. Genetic improvement effects on growth and yield of loblolly pine plantations. *For Sci* 1987;**33**:707–24. https://doi.org/10.1093/forestscience/33.3.707.

Carson SD, Carcia O, Hayes JD. Realized gain and prediction of yield with genetically improved *Pinus radiata* in New Zealand. *For Sci* 1999;**45**:186–200. https://doi.org/10.1093/forestscience/45.2.186.

Charbonneau P, Knapp B. *A user's Guide to PIKAIA 1.0. NCAR Technical Note 418+IA*. Colorado: High Altitude Observatory. National Center for Atmospheric Research, 1995, 121.

Cubbage F, Mac Donagh P, Sawinski JJ. *et al.* Timber investment returns for selected native forests in South America and the southern United States. *New For* 2009;**33**:237–55.

Danescu A, Kohnle U, Bauhaus J. *et al.* Long-term development of natural regeneration in irregular, mixed stands of silver fir and Norway spruce. *For Ecol Manage* 2018;**430**:105–16. https://doi.org/10.1016/j.foreco.2018.07.055.

Das AK, Das S, Ghosh A. Ensemble feature selection using bi-objective genetic algorithm. *Knowl-Based Syst* 2017;**123**:116–27. https://doi.org/10.1016/j.knosys.2017.02.013.

Deng C, Froese R, Zhang S. *et al.* Development of improved and comprehensive growth and yield models for genetically improved stands. *Ann For Sci* 2020;**77**:89. https://doi.org/10.1007/s13595-020-00995-5.

Di Fulvio F, Lessa A. D4.4 Report on EU forest management costing module and green jobs calculator. Horizon-CL5-2021-D1-01 Call. 2025;40. https://www.forestnavigator.eu/wp-content/uploads/FN_D4.4-ForestManagement-costing.pdf

Dubey SD. Some percentile estimators for Weibull parameters. *Technometrics.* 1967;**9**:119–29. https://doi.org/10.1080/00401706.1967.10490445.

Eerikäinen K, Miina J, Valkonen S. Models for the regeneration establishment and development of established seedlings in uneven-aged, Norway spruce dominated forest stands of southern Finland. *For Ecol Manage* 2007;**242**:444–61. https://doi.org/10.1016/j.foreco.2007.01.078.

Eerikäinen K, Valkonen S, Saksa T. Ingrowth, survival and height growth of small trees in uneven-aged *Picea abies* stands in southern Finland. *For Ecosyst* 2014;**1**:1–10.

Faustmann M. Berechnung des Werthes, welchen Waldboden, sowie noch nicht haubare Holzbestände für die Waldwirthschaft besitzen. [calculation of the value which forest land and immature stands possess for forestry]. *Allg Forst Jagdztg* 1849;**25**:441–55.

Gauthier S, Bernier P, Kuuluvainen T. *et al.* Boreal forest health and global change. *Science.* 2015;**349**:819–22. https://doi.org/10.1126/science.aaa9092.

Gitman LJ, Zutter CJ. *Principles of Managerial Finance, Global*. 14th edition. Pearson, London, United Kingdom, 2015, 928.

Goldberg DE. *Genetic Algorithms in Search, Optimization and Machine Learning*. Boston: Addison-Wesley Longman Publishing, 1989, 412.

Gould P, Johnson R, Marshall D. *et al.* Estimation of genetic-gain multipliers for modeling Douglas-fir height and diameter growth. *For Sci* 2008;**54**:588–96. https://doi.org/10.1093/forestscience/54.6.588.

Haapanen M. Performance of genetically improved Norway spruce in one-third rotation-aged progeny trials in southern Finland. *Scand J For Res* 2020;**35**:221–6. https://doi.org/10.1080/02827581.2020.1776763.

Haapanen M, Hynynen J, Ruotsalainen S. *et al.* Realised and projected gains in growth, quality and simulated yield of genetically improved scots pine in southern Finland. *Eur J For Res* 2016;**135**:997–1009. https://doi.org/10.1007/s10342-016-0989-0.

Hadi MRHS, Gonzalez-Andujar JL. Comparison of fitting weed seedling emergence models with nonlinear regression and genetic algorithm. *Comput Electron Agr* 2009;**65**:19–25. https://doi.org/10.1016/j.compag.2008.07.005.

Holland JH. *Adaptation in Natural and Artificial Systems*. Ann Arbor: The MIT Press, 1975, 232.

Hynynen J, Ahtikoski A, Siitonen J. *et al.* Applying the MOTTI simulator to analyse the effect of alternative management schedules on timber and non-timber production. *For Ecol Manage* 2005;**207**:5–18. https://doi.org/10.1016/j.foreco.2004.10.015.

Hynynen J, Eerikäinen K, Mäkinen H. *et al.* Growth response to cuttings in Norway spruce stands under even-aged and uneven-aged management. *For Ecol Manage* 2019;**437**:314–23. https://doi.org/10.1016/j.foreco.2018.12.032.

Hynynen J, Ojansuu R, Hökkä H. *et al. Models for Predicting Stand Development in MELA System*. Helsinki: The Finnish Forest Research Institute Research Papers No. 835, 2002, 116.

Hynynen J, Salminen H, Ahtikoski A. *et al.* Long-term impacts of forest management on biomass supply and forest resource development: A scenario analysis for Finland. *Eur J For Res* 2015;**134**:415–31. https://doi.org/10.1007/s10342-014-0860-0.

Hynynen J, Salminen H, Huuskonen S. *et al. Scenario Analysis for the Biomass Supply Potential and the Future Development of Finnish

Forest Resources. Helsinki: The Finnish Forest Research Institute Research Papers No. 302, 2014, 106.

Hyytiäinen K, Tahvonen O. The effects of legal limits and recommendations on timber production: The case of Finland. *For Sci* 2001;**47**: 443–54. https://doi.org/10.1093/forestscience/47.4.443.

Jansson G, Hansen JK, Haapanen M. *et al.* The genetic and economic gains from forest tree breeding programmes in Scandinavia and Finland. *Scand J For Res* 2017;**32**:273–86. https://doi.org/10.1080/02827581.2016.1242770.

Juutinen A, Ahtikoski A, Lehtonen M. *et al.* The impact of a short-term carbon payment scheme on forest management. *Forest Policy Econ* 2018;**90**:115–27. https://doi.org/10.1016/j.forpol.2018.02.005.

Juutinen A, Shanin V, Ahtikoski A. *et al.* Profitability of continuous cover forestry in Norway spruce-dominated peatland forest and the role of water table. *Can J For Res* 2021;**51**:859–70. https://doi.org/10.1139/cjfr-2020-0305.

Kuuluvainen T, Tahvonen O, Aakala T. Even-aged and uneven-aged forest management in boreal Fennoscandia: A review. *Ambio.* 2012;**7**:720–37.

Laitila J, Heikkilä J, Anttila P. Harvesting alternatives, accumulation and procurement cost of small-diameter thinning wood for fuel in Central Finland. *Silva Fenn* 2010;**44**:465–80.

Lee D, Repola J, Bianchi S. *et al.* Calibration models for diameter and height growth of Norway spruce growing in uneven-aged stands in Finland. *For Ecol Manage* 2024;**558**:121783. https://doi.org/10.1016/j.foreco.2024.121783.

Li MJ, Chen DS, Wang F. *et al.* Optimizing emission inventory for chemical transport models by using genetic algorithm. *Atmos Environ* 2010;**44**:3926–34. https://doi.org/10.1016/j.atmosenv.2010.07.010.

Natural Resources Institute Finland. In Luke Statistics database. *Forest Statistics; Structure and Production; Silvicultural and Forest Improvement Work*, 2023a. Natural Resources Institute Finland (Luke), Helsinki, Finland. https://statdb.luke.fi/PxWeb/pxweb/en/LUKE/ (accessed 14 September, 2023).

Natural Resources Institute Finland. In Luke Statistics database. *Forest Statistics; Economy; Volumes and Prices in Roundwood Trade*, 2023b. Natural Resources Institute Finland (Luke), Helsinki, Finland. https://statdb.luke.fi/PxWeb/pxweb/en/LUKE/ (accessed 14 September, 2023).

Mason WL, Diaci J, Carvalho J. *et al.* Continuous cover forestry in Europe: Usage and the knowledge gaps and challenges to wider adaption. *Forestry.* 2022;**95**:1–12. https://doi.org/10.1093/forestry/cpab038.

Matala J, Hynynen J, Miina J. *et al.* Comparison of a physiological model and a statistical model for prediction of growth and yield in boreal forests. *Ecol Model* 2003;**161**:95–116. https://doi.org/10.1016/S0304-3800(02)00297-1.

Metcalfe TS, Charbonneau P. Stellar structure modeling using a parallel genetic algorithm for objective global optimization. *J Comput Phys* 2003;**185**:176–93. https://doi.org/10.1016/S0021-9991(02)00053-0.

Miettinen J, Hallikainen V, Valkonen S. *et al.* Natural regeneration and early development of scots pine seedlings after gap cutting in northern Finland. *Scand J For Res* 2024;**39**:89–100. https://doi.org/10.1080/02827581.2024.2303022.

Mönkkönen M, Juutinen A, Mazziotta A. *et al.* Spatially dynamic forest management to sustain biodiversity and economic returns. *J Environ Manage* 2014;**134**:80–9. https://doi.org/10.1016/j.jenvman.2013.12.021.

Niinimäki S, Tahvonen O, Mäkelä A. Applying a process-based model in Norway spruce management. *For Ecol Manage* 2012;**265**:102–15. https://doi.org/10.1016/j.foreco.2011.10.023.

O'Hara K. *Multi-Aged Silviculture*. Oxford: Oxford University Press, 2014, 240.

Österberg N, Parkatti VP, Tahvonen O. Comparing stand growth models in optimizing mixed-species forest management. *Scand J For Res* 2023;**38**:353–66. https://doi.org/10.1080/02827581.2023.2227095.

Paques LE. *Forest Tree Breeding in Europe: Current State-of-the-Art and Perspectives*. Dordrecht: Springer, 2013, 527. https://doi.org/10.1007/978-94-007-6146-9.

Parkatti VP. *On the Economics of Continuous Cover and Rotation Forestry. Department of Forest Sciences, Faculty of Agriculture and Forestry*Academic Dissertation,. University of Helsinki, Helsinki, Finland. 2021 Dissertationes Forestales 312. Summary of 37 pages + three original papers.

Parkatti VP, Assmuth A, Rämö J. *et al.* Economics of boreal conifer species in continuous cover and rotation forestry. *Forest Policy Econ* 2019;**100**:55–67. https://doi.org/10.1016/j.forpol.2018.11.003.

Parkatti VP, Tahvonen O. Optimizing continuous cover and rotation forestry in mixed-species boreal forests. *Can J For Res* 2020;**50**: 1138–51. https://doi.org/10.1139/cjfr-2020-0056.

Parkatti VP, Tahvonen O, Viskari T. *et al.* Including soil alters the optimization of forestry with carbon sinks. *Can J For Res* 2023;**53**: 591–604. https://doi.org/10.1139/cjfr-2022-0226.

Peura M, Burgas D, Eyvindson K. *et al.* Continuous cover forestry is a cost-efficient tool to increase multifunctionality of boreal production forests in Fennoscandia. *Biol Conserv* 2018;**217**:104–12. https://doi.org/10.1016/j.biocon.2017.10.018.

Pukkala T. Population-based methods in the optimization of stand management. *Silva Fenn* 2009;**43**:261–74.

Pukkala T, Lähde E, Laiho O. Growth and yield models for uneven-sized forest stands in Finland. *For Ecol Manage* 2009;**258**:207–16. https://doi.org/10.1016/j.foreco.2009.03.052.

Rana P, Juutinen A, Eyvindson K, Tolvanen A. Cost-efficiency analysis of multiple ecosystem services across forest management regimes. *Journal of Environmental Management*, 2024;**370**:122438. https://doi.org/10.1016/j.jenvman.2024.122438.

Rämö J, Tahvonen O. Economics of harvesting uneven-aged forest stands in Fennoscandia. *Scandinavian journal of forest research*, 2014;**29**:777–792. https://doi.org/10.1080/02827581.2014.982166.

Rämö J, Tahvonen O. Optimizing the harvest timing in continuous cover forestry. *Environ Resource Econ* 2017;**67**:853–68. https://doi.org/10.1007/s10640-016-0008-4.

Richards FJ. A flexible growth function for empirical use. *J Ext Bot* 1959;**10**:290–301. https://doi.org/10.1093/jxb/10.2.290.

Sabatia CO, Burkhart HE. Height and diameter relationships and distributions in loblolly pine stands of enhanced genetic material. *For Sci* 2013;**59**:278–89. https://doi.org/10.5849/forsci.11-093.

Salminen H, Lehtonen M, Hynynen J. Reusing legacy FORTRAN in the MOTTI growth and yield simulator. *Comput Electron Agr* 2005;**49**: 103–13. https://doi.org/10.1016/j.compag.2005.02.005.

Siipilehto J. Height distributions of scots pine sapling stands affected by retained tree and edge stand competition. *Silva Fenn* 2006;**40**: 473–86.

Sinha A, Rämö J, Malo P. *et al.* Optimal management of naturally regenerating uneven-aged forests. *Eur J Oper Res* 2017;**256**: 886–900. https://doi.org/10.1016/j.ejor.2016.06.071.

Statistics Finland. *A Statistical Database*, 2023. Cost-of-living index, 1951;10=100, annual data. Statistics Finland (Tilastokeskus in Finnish), Helsinki, Finland. https://pxdata.stat.fi (accessed 14 September, 2023).

Tahvonen O, Pihlainen S, Niinimäki S. On the economics of optimal timber production in boreal scots pine stands. *Can J For Res* 2013;**43**:719–30. https://doi.org/10.1139/cjfr-2012-0494.

Tahvonen O, Pukkala T, Laiho O. *et al.* Optimal management of uneven-aged Norway spruce stands. *For Ecol Manage* 2010;**260**: 106–15. https://doi.org/10.1016/j.foreco.2010.04.006.

Tahvonen O, Rämö J. Optimality of continuous cover vs. clear-cut regimes in managing forest resources. *Can J For Res* 2016;**46**: 891–901. https://doi.org/10.1139/cjfr-2015-0474.

Tahvonen O, Suominen A, Malo P. *et al.* Optimizing high-dimensional stochastic forestry *via* reinforcement learning. *J Econ Dyn Control* 2022;**145**:104553. https://doi.org/10.1016/j.jedc.2022.104553.

Tahvonen O, Suominen A, Parkatti VP. *et al.* Optimizing high-dimensional forestry for wood production and carbon sinks. *Can J For Res* 2024;**54**:877–94. https://doi.org/10.1139/cjfr-2023-0267.

Tahvonen O. Economics of rotation and thinning revisited: the optimality of clearcuts versus continuous cover forestry. *Forest policy and Economics*, 2016;**62**:88–94. https://doi.org/10.1016/j.forpol.2015.08.013.

Tonteri T, Hotanen JP, Kuusipalo J. The Finnish forest site type approach: Ordination and classification studies of Mesic forest sites in southern Finland. *Vegetatio* 1990;**87**:85–98. https://doi.org/10.1007/BF00045658.

Valkonen S, Giacosa LA, Heikkinen J. Tree mortality in the dynamics and management on uneven-aged Norway spruce stands in southern Finland. *Eur J For Res* 2020;**139**:989–98. https://doi.org/10.1007/s10342-020-01301-8.

Vuokila Y, Väliaho H. Viljeltyjen havumetsiköiden kasvatusmallit. *Comm Inst For Fenn* 1980;**99**:1–271.

Weitzman ML. Risk-adjusted gamma discounting. *J Environ Econ Manag* 2010;**60**:1–13. https://doi.org/10.1016/j.jeem.2010.03.002.

White T, Adams W, Neal D. *Forest Genetics*. Oxford University Press, Oxford, United Kingdom, 2007, 591. https://doi.org/10.1079/9781845932855.0000.

Xie CY, Yanchuk AD. Breeding values of parental trees, genetic worth of seed orchard seedlots, and yields of improved stocks in British Columbia. *West J Appl For* 2003;**18**:88–100. https://doi.org/10.1093/wjaf/18.2.88.

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