Forestry: An International Journal of Forest Research, 2023, 1–12
https://doi.org/10.1093/forestry/cpad038
Original Article

Assessing the suitability of under-represented tree species for multifunctional forest management—an example using economic return and biodiversity indicators

Benjamin Gang*, Logan Bingham, Elizabeth Gosling and Thomas Knoke

Institute of Forest Management—Department of Life Science Systems, Technical University of Munich, Hans-Carl-von-Carlowitz-Platz 2, 85354 Freising, Germany
*Corresponding author. Department of Life Science Systems—Institute of Forest Management, Technical University of Munich, Hans-Carl-von-Carlowitz-Platz 2, 85354 Freising, Germany. E-mail: benjamin.gang@tum.de

Abstract

A shifting focus in forest management from timber production to resilience and multifunctionality in the face of changing disturbance regimes might entail altering the species composition of forests. Although the conifers Douglas fir (*Pseudotsuga menziesii*) and silver fir (*Abies alba*) currently comprise only a small proportion of Central European forests, the prospect of widespread planting of these species as a climate adaptation measure is currently widely debated by forest managers. To inform this debate, objective assessments of the multifunctional value of these species are required. Here, we introduce Pareto frontiers to objectively assess the value of tree species under competing objectives and considering an uncertain future. Using these frontiers, we explore trade-offs between financial performance and biodiversity aspects of German tree species portfolios with and without these currently rare conifers. We compare several potential biodiversity indicators (related to herbivores, saproxylic beetles, and deadwood decomposition rates) that can be derived from standard forest inventory data. Our results indicate that optimizing the biodiversity indicators generates gradual decreases in financial performance at first, but after an inflection point soil rent declines sharply. Portfolios excluding Douglas fir and silver fir achieved comparable biodiversity levels, but much weaker financial performance, than portfolios that included these conifers. Our novel approach of generating Pareto frontiers that integrate uncertainty can offer useful insights into ecosystem services trade-offs in contexts where risk is unequally distributed across management alternatives.

Keywords: Pareto frontiers; robust optimization; tree species selection; multifunctional forest management; biodiversity; soil rent

Introduction

The composition of productive forests in Central Europe is and will continue to be shaped both by strategic choices about land area allocation and species selection, as well as management and silvicultural decisions like harvesting, thinning, and regeneration (Luyssaert et al. 2018, Sousa-Silva et al. 2018). Simultaneously promoting resilience and multifunctionality may require increasing the share of tree species that are currently rare or under-utilized into existing forest portfolios (Thurm et al. 2018, Knoke et al. 2022b). However, determining the optimal mix is complicated by the uncertainty about future climatic, environmental and economic conditions as well as due to the diverse preferences and priorities of decision-makers (Díaz-Yáñez et al. 2021).

In Germany, climate change is expected to sharply restrict the suitable distribution range of major commercial species like Norway spruce (*Picea abies*) and Scots pine (*Pinus sylvestris*), displacing their ideal growing conditions northward and to higher elevations (Hanewinkel et al. 2010, 2022). One option for filling the resulting gaps is planting fast-growing, resilient, and profitable conifers like Douglas fir and silver fir. These species currently constitute less than 2% of the German forest portfolio (Federal Ministry of Food and Agriculture 2014, Vitali et al. 2017).

In debates about this species-transition proposal, economic objectives, like the continued competitiveness of the forestry sector, often clash with environmental ones, like the risk of disrupting ecological networks through large-scale species introduction (Goßner and Ammer 2006, Wolgemuth et al. 2021), even if the risk of invasiveness is low (Bindewald et al. 2021). These debates resist impartial analysis partly because they involve subjective disagreements about how economic objectives should be weighted relative to environmental ones, but also because management alternatives designed to pursue those objectives entail different types and magnitudes of risk (Pötzelsberger et al. 2020). For example, it might be possible to increase short-term carbon storage by declining to harvest mature trees or promoting overstocked stands, but only at the cost of elevated susceptibility to natural disturbances like windthrow and wildfire, which—if they were to occur—could accelerate and magnify carbon release (Temperli et al. 2020, Herbert et al. 2022).

Subjective debates about criteria weights can sometimes be clarified through quantitative trade-off analysis, e.g. using optimization to calculate the economic opportunity cost associated with managing for a higher provision of non-market ecosystem services. Pareto frontier tools have shown a particular potential

Handling Editor: Dr. Fabian Fassnacht
Received: October 5, 2022. **Revised:** July 7, 2023. **Accepted:** July 9, 2023

for this type of problem. Unlike the decision support models traditionally used in forest management, which aim to identify a single optimal solution given a set of decision variables with *a priori* weights, Pareto methods instead solve for every possible combination of criteria weights to generate a trade-off curve or "possibility frontier" (Marto et al. 2018, Kaim et al. 2021) along which no criterion can be improved without worsening another (Borges et al. 2014). Exploring these frontiers enables policymakers, stakeholders, and forest managers to evaluate a continuum of potentially optimal solutions and critically evaluate how different weighting schemes influence alternative future forests (Marques et al. 2021).

Unfortunately, the forest management literature currently lacks versatile Pareto frontier tools that effectively integrate uncertainty and communicate risk information to decision-makers. This is a major limitation when it comes to evaluating climate adaptation strategies because the expectation of a changing risk environment is what motivates decision-makers to deviate from business-as-usual in the first place. Thus, trade-offs between environmental and economic objectives (which current Pareto tools address) are inseparable from issues of risk and uncertainty (which they do not).

Here, we describe a new approach based on Pareto frontiers that are robust to future uncertainty, meaning that they only represent decision outcomes that are attainable even under worst-case conditions. In the following, we demonstrate how this approach can inform debates about environmental-economic trade-offs by applying it to the species-transition example described above: specifically, we analyze how increasing the share of Douglas fir and silver fir impacts the performance of German forest portfolios as measured by financial and biodiversity metrics. To highlight the multidimensional nature of biodiversity (and to show how our approach can be readily adapted to different contexts), we replicate the analysis with several example biodiversity indicators that can be derived from forest inventory data. To our knowledge, this is the first use of Pareto frontiers based on robust optimization in a forest management context.

Methods

Overview

This study evaluates portfolios consisting of six potential tree species, four common commercial species [Norway spruce, European beech (*Fagus sylvatica*), Scots pine, English oak (*Quercus robur*)] plus two currently rare species (Douglas fir and silver fir), that could play a key role in future portfolios (Vitali et al. 2017). To generate Pareto frontiers that integrate uncertainty, we first used multi-objective robust optimization to identify the species portfolio that maximizes financial performance within a given uncertainty space (Fig. 1). We then introduced biodiversity as a second objective and progressively increased its weight in steps of 5% until we obtained the portfolio that maximizes biodiversity without regard to financial performance. We replicated this process with several alternative biodiversity indicators, as well as for portfolios including and excluding Douglas fir and silver fir as candidates. This allows us to calculate not only the financial opportunity costs associated with incremental increases in biodiversity score, but also to examine how currently rare species and indicator selection impact the geometry of the trade-off curves. Here, we define opportunity costs as the difference in achieved soil rent achieved by the financially optimized portfolio (not including biodiversity) and each biodiversity scenario.

To address uncertainty, we consider ranges of possible values that our indicators might achieve in the future. These span from the assumed worst-case value to the expected mean value. The worst case is obtained by subtracting 2.5 times the standard deviation (resulting from Monte Carlo simulations) from the average indicator value. The standard deviation reflects stand failure caused by natural hazards, such as storms, bark beetles, drought, or snow breakage. Moreover, it also reflects the fluctuation of timber prices. However, note that we do not make assumptions on the probability of specific values inside the considered intervals; we rather require that our robust solutions remain feasible for all indicator values included in the intervals (Knoke et al. 2016).

Model formulation

We formulate our multi-objective robust optimization model as follows:

$$\min \beta^s \tag{1}$$

$$\beta^s = \max_a \{D^s_u\} \tag{2}$$

$$\beta^b = 0.95, 0.90, 0.85, 0.80, 0.75, 0.70 \ldots \tag{3}$$

$$D^s_u = \frac{\max y^s_u - \sum_{t=1}^{6} a_t y^s_{tu}}{\max y^s_u - \min y^s_u} \tag{4}$$

$$\beta^s \geq D^s_u \forall u \tag{5}$$

$$\beta^b \geq D^b_{iu} \forall i, u \tag{6}$$

$$D^b_{iu} = \frac{\max y^b_{iu} - \sum_{t=1}^{6} a_t y^b_{itu}}{\max y^b_{iu} - \min y^b_{iu}} \quad i = 1, 2, 3 \tag{7}$$

$$y^s_{tu} = \begin{cases} y^s_t \\ y^s_t - 2.5 \cdot S^s_t \end{cases} \tag{8}$$

$$y^b_{itu} = \begin{cases} y^b_{it} \\ y^b_{it} - 2.5 \cdot S^b_{it} \end{cases} \tag{9}$$

$$\sum_{t=1}^{6} a_t = 1 \tag{10}$$

$$a_t \geq 0 \tag{11}$$

We express financial performance in terms of *soil rent (s)*, which refers to the annuity of the soil expectation value (Table 1). We define the *underperformance* β^s of a portfolio as the maximum relative distance between the soil rent it achieves and the highest soil rent that could be expected under a best-case scenario. This method builds on the relative distances D^s_u and D^b_{iu}, which measure the underperformance of soil rent and the biodiversity indicators in a specific uncertainty scenario u. These distances depend on the allocation of stand type proportions a_t to our tree species. To integrate uncertainty, the model considers two input parameters per tree species, t and objective, i, the nominal soil rent y^s_t or biodiversity indicators y^b_{it} and a worst-case value consisting of the nominal value minus the product of $m_u = 2.5$ times the standard deviations S^s_t and S^b_{it}. This is a moderate level of uncertainty, while $m_u = 2.0$ (representing more optimistic decision-makers, who expect less strong decreases of the indicator level in the worst case) (Knoke et al. 2016, Uhde et al. 2017) or $m_u = 3.0$ (for more pessimistic decision-makers) (Gosling et al. 2021, Knoke et al. 2022a) have been used in previous applications of the robust multi-objective optimization method that our paper expands and

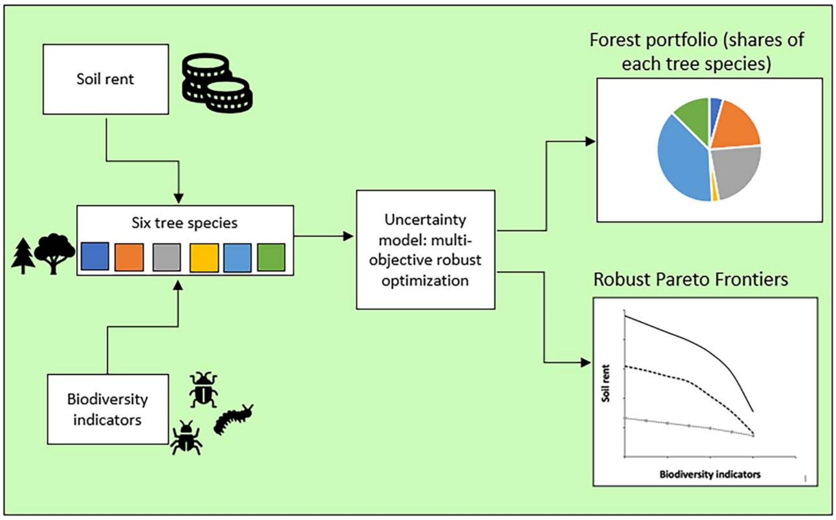

Figure 1. Graphical illustration of the approach.

Table 1. Description of each variable used in the optimization approach.

β^s	Minimized maximal relative distance between the achieved value and the most desirable value of the soil rent *s* across all uncertainty scenarios *u*
$\mathbf{a}$	Vector of six decision variables representing the optimized proportions of the six considered tree species
a_t	Proportion of the tree species in the given forest portfolio (decision variable)
D_u^s	Relative distance between the achieved value and the most desirable value of the soil rent for uncertainty scenario *u*
β^b	Tolerated maximal relative distance between the achieved value and the most desirable value across three different biodiversity (*b*) indicators ($i = 1, 2, 3$) and all uncertainty scenarios *u*, stepwise obtaining values of 0.95, 0.90, 0.85, 0.80, 0.75, and smaller
$\max y_u^s$	Maximum soil rent in uncertainty scenario *u*
y_{tu}^s	Soil rent of stand type *t* in uncertainty scenario *u*
$\min y_u^s$	Minimum soil rent in uncertainty scenario *u*
D_{iu}^b	Relative distance between the achieved value and the most desirable value of biodiversity indicator *i* for uncertainty scenario *u*
$\max y_{iu}^b$	Maximum level of biodiversity indicator *i* in uncertainty scenario *u*
y_{itu}^b	Value of biodiversity indicator *i* for stand type *t* in uncertainty scenario *u*
$\min y_{iu}^b$	Minimum level of biodiversity indicator *i* in uncertainty scenario *u*
y_t^s	Nominal (expected) value of the soil rent of stand type *t*
$m_u S_t^s$	Multiplier ($m_u = 2.5$) times standard deviation S_t^s of the soil rent of stand type *t*
y_{it}^b	Nominal (expected) value of biodiversity indicator *i* for stand type *t*
$m_u S_{it}^b$	Multiplier ($m_u = 2.5$) times standard deviation S_{it}^b of biodiversity indicator *i* for stand type *t*

develops. With our robust model, we minimize the maximum relative distance (called underperformanceβ^s) between the highest possible soil rent and the soil rent that is actually achieved by a portfolio of forest stand types with the given uncertainty scenario *u*, conditional to predefined acceptable levels of underperformance β^b for $i = 1, 2, 3$ biodiversity indicators (equations (1–11)). By using different predefined acceptable levels of underperformance for the biodiversity indicators and minimizing the underperformance of the soil rent β^s for each required biodiversity level, we construct Pareto frontiers indicating the optimal tree species composition (shares of proportions a_t allocated to stand types with $\sum_{t=1}^{6} a_t = 1$) for a hypothetical forest enterprise for achieving multiple objectives.

To draw the Pareto frontiers, we use the maximum guaranteed soil rent given increasing required levels of biodiversity. To find the guaranteed performance levels for soil rent (P^s), we subtracted the optimized underperformance β^s stepwise from 100; we did the same with P^b for biodiversity. It is computed as follows:

$$P^s = 100 - \beta^s \tag{12}$$

$$P^b = 100 - \beta^b \tag{13}$$

For each set of indicators and tree species considered (in total 21 different optimizations per indicator tested), we gradually tightened the constraint in 5% increments, i.e. $\beta^b = 0.95, 0.90, 0.85, 0.80, 0.75, 0.70$, which implies giving biodiversity increasingly higher weights. We developed a macro in Visual Basic to iteratively compute each of the in total 12 Pareto frontiers.

Indicator set

To demonstrate how our method can be adapted to different decision contexts, we carried out a series of example optimizations using different combinations of four potential indicators (Mazziotta et al. 2017) (Table 2). All indicators have a constant value for each tree species, i.e. the values they take are exclusively a function of how area is allocated to each species. This simplification ignores potential non-linear ecological interactions because the optimization is designed to utilize standard inventory data at the portfolio level, where spatial information is typically not available. This prototype model version thus excludes ecological complexities, which lead to non-linearities. We address this issue in the discussion below.

We obtained expected soil rent per hectare and year (€ ha^{-1} year^{-1}) for five tree species from Knoke et al. (2017) as well as

Table 2. Tree species specific indicator values and standard deviation (S) used in the optimization.

	Economic indicator		Biodiversity indicators					
Tree species	**Soil rent ($€ \, ha^{-1} \, year^{-1}$)**	**S^s**	**Herbivore species (N)**	**S_1^b**	**Saproxylic beetle (N)**	**S_2^b**	**Average decay rate ($g \, cm^{-3}$)**	**S_3^b**
Beech	8	33	333	53	14	1.9	0.069	0.043
Oak	−3	31	913	227	26	4.3	0.021	0.021
Douglas fir	530	199	33	1	19	2.6	0.002	0.0270
Scots pine	−38	45	410	75	18	2.5	0.015	0.023
Spruce	201	85	353	58	21	3.0	0.035	0.034
Silver fir	187	60	207	22	8	0.9	0.020	0.020

from Knoke et al. (2020) for silver fir. Soil rent is the annuity of the soil expectation value. The data represent site conditions of southeastern Bavaria and were based on forest growth simulations using the model SILVA (Pretzsch et al. 2002). The simulations used in Knoke et al. (2017) consider prototype survival models later established by Brandl et al. (2020) who used a pan-European data set to parameterize accelerated failure time models for the survivability of six important European tree species. The negative soil rent for English oak and Scots pine follows the assumption that the planting costs exceed the appropriately discounted future returns. Generally, conifers are more profitable than hardwoods due to higher timber prices and shorter rotation lengths, but conifers are also subject to higher disturbance-related risks (Knoke et al. 2017). For instance, Douglas fir has the highest mean soil rent, but also by far the highest absolute standard deviation.

Measuring biodiversity

Biodiversity is a multidimensional concept, and biodiversity science has revealed rich and complex interactions.

When formulating long-term strategic plans, policymakers, forest enterprises, and managers often make decisions about species portfolio by consulting basic forest inventories that contain either extremely coarse spatial data or, more commonly, no spatial data at all. Consequently, at this stage, they consider how much of which species to invest in (i.e. harvest or plant), while deferring decisions about where exactly to plant each individual tree until later tactical planning and implementation stages. This is because only rough biodiversity assessments are currently possible during portfolio building. At this stage, the aim is not to design a biodiverse or ecologically complex stand, but rather to maximize the available strategic possibility space by providing managers with the ingredients to design biodiversity supporting tactical plans later. With these considerations in mind, we sought indicators that (i) reflect species selection decisions, (ii) can be derived from standard inventory data, and (iii) highlight the importance of indicator choice by illustrating trade-offs between different measures of biodiversity.

We tested three biodiversity indicators, an aggregate indicator combining all of them, and performed a sensitivity analysis on the importance of indicator direction (e.g. “more deadwood is better” versus “less deadwood is better”). We stress that these indicators are just examples to illustrate the method. If more detailed data are available in a given decision setting, these indicators can be exchanged for new or better ones without impacting the functioning of our model, although more complex input data might entail higher computational costs.

The first biodiversity indicator we used is based on the preferences of herbivores for different tree species. We obtained correlations between different tree genera and the number of herbivorous species identified on each in a forthcoming study by ecologists Gossner and Brändle, which we cross-referenced against previous work on the topic (Brändle and Brandl 2001, Gossner et al. 2016). For instance, oak is associated with the highest number of herbivorous species (913) and Douglas fir with the lowest (33). Based on these data, we evaluated the possible contribution of each tree species to the diversity of herbivore communities.

The second biodiversity indicator is based on the relative decomposition rate of deadwood, which varies from species to species (Kahl et al. 2017) assuming similar size and environmental conditions. Faster decomposition suggests higher metabolic activity and a greater number of organisms. Of the species we considered, beech has the highest decomposition rate (average decrease in wood density g cm^{-3}) under typical German conditions, followed by spruce and oak (Kahl et al. 2017). The decomposition rate for silver fir could be complemented from a Slovenian study according to Přívětivý et al. (2018) in relation to spruce.

The third biodiversity indicator was the number of saproxylic (i.e. deadwood-dependent) beetles per tree species from Vogel et al. (2020), who analyze the early phase of wood decay by exposing branches of a standard length and diameter from 42 tree species and counting beetles associated with each. Saproxylic beetles distribute themselves unevenly across the tree species we consider.

The share of the different tree species is the result (not the input) of our optimization. The share of a specific tree species depends on the individual indicator values and the standard deviation of each tree species. The solution algorithm in the Excel OpenSolver we used is based on a common technique for solving linear programming problems called the simplex method (Mason 2012). This gives a definite and exact solution (unlike the approximations produced by heuristic techniques), but it does not require testing every possible combination of shares. In optimization terminology, that would be a “combinatorial” problem that would not be computationally tractable at this size and, even if it were, would not give a better solution. Instead, the simplex algorithm works by evaluating vertices in the feasible region—this shrinks the problem size and also identifies the optimal solution with mathematical certainty.

Results

Trade-offs between biodiversity and soil rent

To evaluate how each of the currently rare conifers influences portfolio performance, we compare Pareto frontiers representing the trade-offs between soil rent and the aggregated biodiversity

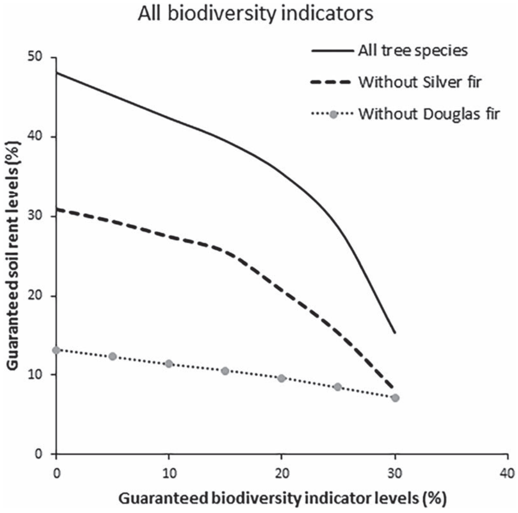

Figure 2. Pareto frontiers showing the guaranteed biodiversity level vs. the guaranteed level of soil rent considering all biodiversity indicators aggregated.

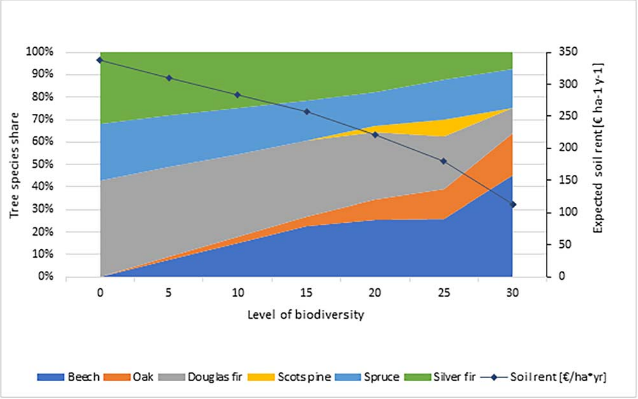

Figure 3. Tree species composition and achieved soil rent with increasing level of biodiversity.

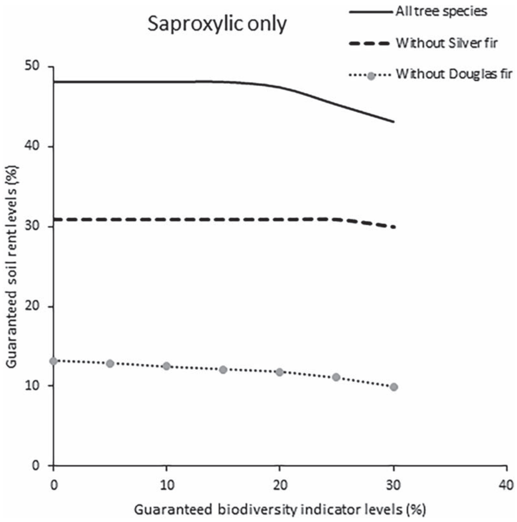

Figure 4. Influence of the biodiversity indicator saproxylic beetles on guaranteed level of soil rent.

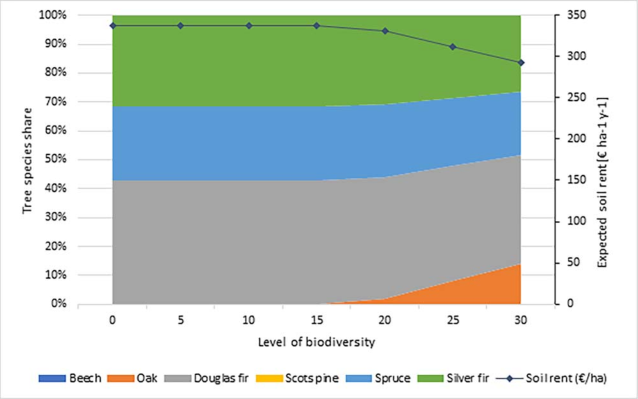

Figure 5. Tree species composition and achieved soil rent with increasing level of biodiversity considering the biodiversity indicator saproxylic beetles only.

indicator for stand type portfolios consisting of all six tree species, and portfolios excluding either silver fir or Douglas fir (Fig. 2). Broadly speaking, the guaranteed soil rent first slightly declines as the level of required biodiversity increases. However, after a certain inflection point additionally biodiversity gains come at increasing marginal cost (i.e. small gains in biodiversity have a growing negative financial impact). This inflection point usually occurs when we require at least ~20%–25% of the maximum biodiversity score, although excluding silver fir moves the inflection point closer to 15%. Excluding Douglas fir has an even more dramatic effect, immediately reducing the performance floor for soil rent by ~35% relative to the six-species portfolio. Uncertainty is implicitly included in all Pareto frontiers, as these reflect minimum performance levels, which are guaranteed given assumptions about the uncertainty space. That is, these solutions offer outcomes that are always achieved or exceeded regardless of which combination of input indicator values is used, if these input values are included in the predefined uncertainty set.

Consistent with previous research, increasing the minimum biodiversity requirement also has a strong diversifying effect on the portfolio composition (Jarisch et al. 2022) (Fig. 3). The area fraction allocated to hardwoods grows with increasing biodiversity requirements. Requiring at least 30% of the maximum biodiversity score using the aggregate indicator generates a portfolio dominated by beech (to which 45% of the total area is allocated), at an opportunity cost of 225€ ha^{-1} year^{-1} relative to the financially optimal portfolio. Reducing the acceptable biodiversity level to 25% of the maximum, however, generates the most diverse portfolio, with all six species represented.

To highlight the importance of indicator selection, we also compare frontiers generated using each of our biodiversity indicators separately. For instance, measuring biodiversity in terms of saproxylic beetles yields a fairly gentle trade-off curve (Fig. 4), indicating that satisfying this indicator is relatively cheap. This is likely because the profitable Douglas fir can support high levels of saproxylic beetles, with oak being introduced only with high biodiversity requirements (Fig. 5). In other words, the saproxylic beetle indicator does not force large deviations from the species composition of the financially optimized portfolio.

In our analysis, Douglas fir has a consistently high performance and tends to dominate the optimal portfolios under a wide range of assumptions. Only when we increase the minimum biodiversity score requirement above 20% does the model introduce oak into the portfolio (here with a share of 14%) (Fig. 5). Thus, the opportunity cost of demanding moderate biodiversity levels are quite low: including the saproxylic beetle indicator as a decision variable only slightly changes the results compared to the

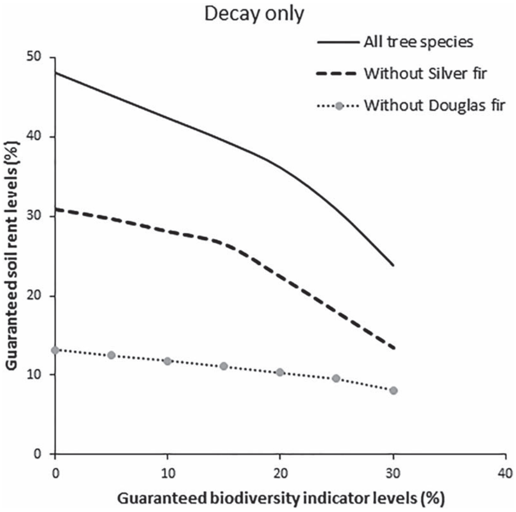

Figure 6. Influence of the biodiversity indicator decay rate on guaranteed level of soil rent (if "more is better").

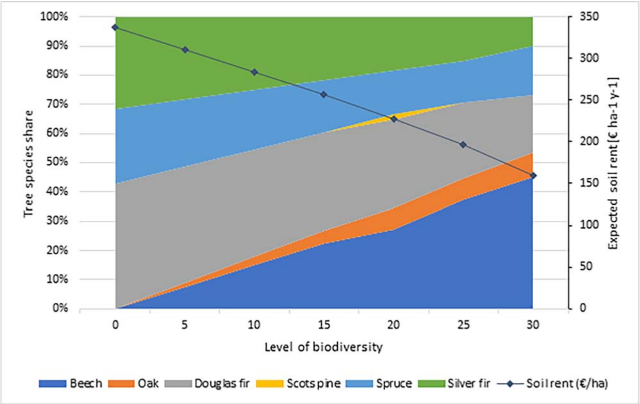

Figure 7. Tree species composition and achieved soil rent with increasing level of biodiversity considering the biodiversity indicator decay rate only (if "more is better").

baseline economics-only scenario, due to the persistently high share allocated to Douglas fir.

Substituting deadwood decomposition rate (with the direction "more is better") for saproxylic beetles as the biodiversity indicator, however, produces a steep trade-off curve that closely resembles the aggregate indicator. Comparing the individual biodiversity indicators confirms that the trade-off between economic and biodiversity performance is mostly driven by the decay indicator (Fig. 6).

In this scenario (here measuring biodiversity in terms of deadwood decay rate), the final tree species portfolio (at a biodiversity level of 30%) consists of 45% beech, 9% oak, 19% Douglas fir, 17% spruce, and 10% silver fir (Fig. 7). With that composition, the achieved soil rent is 159€ ha^{-1} $year^{-1}$. That means the opportunity costs can be numbered with 178€ ha^{-1} $year^{-1}$ in comparison with the purely economic optimized portfolio.

Regardless of which biodiversity indicator is chosen, however, excluding either or both of the currently rare conifers generates a large and immediate economic loss.

Sensitivity analysis

In addition to indicator selection, we also assessed the impact of changing indicator direction. For the decay rate indicator, we considered a scenario where the longer deadwood is in the forest the better it is for the biodiversity (see e.g. Purahong et al. (2017)). Changing from "more decay is better" to "less decay is better" favors Douglas fir, while beech is progressively excluded with higher biodiversity requirements (Fig. 8).

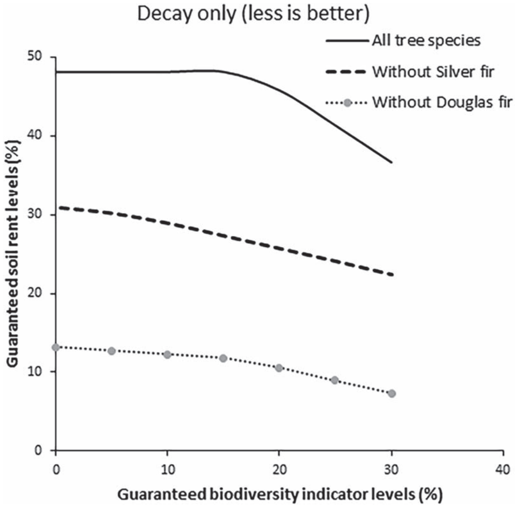

Figure 8. Pareto frontiers with changed direction of the biodiversity indicator decay rate to "less is better".

Discussion

Comparison of species portfolios

Our results suggest that continuing to exclude under-represented conifers like Douglas fir and silver fir from future forest portfolios could significantly lower the economic "floor"—that is, the performance that can be expected even under worst-case conditions—of German forests over a large range of guaranteed biodiversity levels. Conversely, incorporating either species (but especially Douglas fir) into species portfolios can generate Pareto improvements: higher financial returns without any cost to biodiversity (at least as measured by the example indicators examined here). This suggests that these currently under-utilized tree species could contribute to the financial performance of German forestry while supporting elevated levels of biodiversity under ecological-economic uncertainty.

In a purely economic optimization that ignores biodiversity, the portfolio composition is dominated by conifers, and especially Douglas fir, which is profitable and more drought tolerant than spruce (Vitali et al. 2018, Brandl et al. 2020). Increasing the minimum required biodiversity performance among the biodiversity indicators, however, progressively shifts the portfolio composition toward hardwoods, particularly beech. Because hardwoods tend to require longer rotations and generate lower margins, this entails a reduction in financial performance but a more diversified species portfolio (Fig. 3).

The portfolio composition stabilizes when the normalized attainment of the aggregate biodiversity indicator is fixed at a 25% level. The opposite extreme of the Pareto frontier represents a scenario where economic considerations are ignored and the model seeks to maximize biodiversity for its own sake. Unsurprisingly, this further reduces financial performance, largely by eliminating Douglas fir. Note that this discussion refers specifically to the aggregate of the three biodiversity indicators since individually they exert different pressures on the optimal portfolio composition. For instance, focusing on saproxylic beetles mitigates the ecological-economic trade-off, whereas optimizing for the decay rate indicator strongly favors beech and thus comes at a high economic cost (if more is better).

The fact that portfolio diversity is maximized in the intermediate zone of the Pareto frontier (i.e. compromise solutions accounting for both financial performance and biodiversity more or less equally) is significant from a robustness perspective. Multifunctionality requires diversification, which also offers a hedge against uncertainty known as the "insurance effect" (Friedrich et al. 2021). For instance, Jarisch et al. (2022) note that increasing the uncertainty space has a similar diversifying effect as introducing additional indicators. Thus, even though every point on the Pareto frontier is equally efficient depending on the weight assigned to each objective by the decision-maker, the balanced species portfolios that emerge from compromise solutions may prove more robust in the face of future uncertainty.

The tree species portfolio optimized for financial performance alone achieves a soil rent of 337€ ha^{-1} $year^{-1}$, which represents our baseline scenario. As we can see in Fig. 2, the soil rent drops significantly after the level of biodiversity exceeds 20% points. At this point, the opportunity costs in comparison to the baseline portfolio are 116€ ha^{-1} $year^{-1}$. But moving just 10% points further on the efficiency line almost doubles the opportunity costs to 225€ ha^{-1} $year^{-1}$.

Such inflection points in the cost curves are likely to be a significant consideration even for decision-makers who are interested in supporting biodiversity while maintaining robustness. Portfolios requiring biodiversity attainments of at least 20% automatically include all six tree species, contributing to buffering against disturbance risks (Knoke et al. 2016).

Modeling multi-objective decisions under uncertainty

A key innovation of our approach is that it utilizes guaranteed (rather than theoretically optimal) performance levels as target outcomes in the presence of uncertainty. By minimizing the largest disparity between the best attainable outcome and the actually achieved outcome, we maximize performance under worst-case conditions, thereby providing solutions that are guaranteed for both biodiversity and economic objectives. It is important to note that such solutions are guaranteed contingent on the size of a predefined uncertainty space. This means that if the decision-maker's expectations about the worst possible result for any indicator are too optimistic (i.e. an unrealistically small uncertainty space is used), then actual performance could fall short of our robust solutions. However, by using 2.5 times the standard deviation to estimate worst-case values, we have here constructed quite generous uncertainty spaces. In any case, we expect that this approach can serve as an effective means to communicate the uncertainties and robustness of the proposed solutions to stakeholders.

In forestry, many decision support tools are designed to identify a single optimal solution given a set of constraints and decision variables, with the importance of each decision variable being modified by a coefficient (Rönnqvist et al. 2015, França et al. 2022). These coefficients can function as *a priori* criteria weights, especially when the decision-maker's objectives include conflicting and potentially incommensurable values, such as trading off financial performance against an ordinal biodiversity metric (Dyckhoff and Souren 2022). While not necessarily problematic in well-defined decision contexts, this can be limiting in multi-stakeholder settings featuring competing preferences and priorities for non-market values that are difficult to quantify (Farley and Kish 2021). For instance, it could be counterproductive to ask stakeholders to debate criteria weights before they have a clear idea of how the solution will change in response to different weighting schemes (Greco et al. 2019). Indeed, even a single decision-maker might struggle to quantitatively assign weights that accurately represent their aggregate preference functions, especially if their preferences are poorly developed, non-additive, and/or non-independent (Louviere and Meyer 2017). Decision support tools geared toward identifying a single optimal solution in multicriteria contexts generally (and sometimes controversially) assume a rational decision-maker for whom discrete preferences for various attributes can be summed to identify the best alternative (Paul et al. 2019, Eggers et al. 2022). Although this simplifying assumption can offer a reference point, it has a limited correspondence with many human decision processes and can be a poor predictor of real-world choice behavior (Arnott and Gao 2019).

An innovative study by Marques et al. (2021) involving a Pareto frontier-based participatory decision approach illustrates this challenge. The decision space includes dimensions corresponding to ecosystem services like wood production, erosion, and carbon stock, plus a dimension representing the resistance of the landscape to catastrophic wildfire. One of these dimensions is not like the others: when stakeholders are asked to evaluate the first three objectives, they are engaged in a classic discrete choice trade-off problem, but the fire resistance indicator introduces risk. By changing the value of this indicator, stakeholders explicitly make trade-offs not only between different things they want, but also between what they want and the probability of getting anything at all. This new layer of information is likely to make choice tasks significantly more challenging and preferences more difficult to infer, and it can be difficult to effectively communicate this information to stakeholders (Dekker et al. 2016, Dickinson et al. 2020). Scenarios like this are one reason that scholars continue to stress the importance of developing tools for integrating and representing uncertainty in the context of multicriteria trade-off analysis (Sierra-Altamiranda et al. 2020, Couture et al. 2021), including in the design of incentive mechanisms (Kindu et al. 2022).

This requires not only mathematically integrating uncertainty into management planning optimization, but also representing uncertainty in an understandable way to stakeholders and decision-makers. For the first component, forest management planning has drawn on disciplines like operations research and finance in order to develop a range of optimization tools that incorporate risk and uncertainty to identify optimal management prescriptions (Yousefpour et al. 2012, Yousefpour and Hanewinkel 2016, Messerer et al. 2017). These methods differ in terms of their complexity and data requirements, and thus the appropriate approach for a given problem can depend on the degree of uncertainty. For instance, Markowitz-style portfolio optimization models express asset volatility in terms of standard deviations in historical asset performance, but require data about the potential covariances between different assets in a portfolio (in our case, assets correspond to tree species) (Dragicevic et al. 2016, Knoke 2017, West et al. 2021). When uncertainty involves finding an optimal path during a later stage, after an unexpected event has caused a deviation from the original plan, dynamic programming with reverse solution methods are sometimes used, although they are often too computationally intensive to be preferred if a multistage decision process is not a requirement (Chung 2015). If probability distributions are available for potential outcomes, then stochastic programming can sometimes identify risk-integrated solutions that achieve objective function values, which are fairly close to those obtained through deterministic models, but these solutions can be sensitive to the occurrence of unlikely events (Eyvindson and Kangas 2018). Relative to these approaches, robust optimization is targeted at decision contexts involving deep uncertainty, where different potential futures can be identified but not necessarily ranked in terms of their relative likelihood (Augustynczik et al. 2018, 2020, Jarisch et al. 2022).

We chose to implement a robust model for two reasons. First, because it aims to maximize performance under the worst-case scenario, robust optimization does not require probability distributions (unlike stochastic programming) or asset covariances (unlike Markowitz models). Instead, it works with standard deviations of potential performance, which makes it well suited to scenarios with deep uncertainty and risk-averse decision-makers. Second, relative to other approaches to addressing uncertainty mathematically, we think that robust optimization is particularly good fit for Pareto methods because it communicates information that stakeholders can easily understand, namely, the performance floor (i.e. the value that is guaranteed, even in the worst-case scenario of uncertainty spaces). To our knowledge, this study is the first that suggests to visualize frontiers based on robust Pareto sets in the forestry context.

Biodiversity indicator selection

Biodiversity is an important public good, and state forests in Germany are required to consider it appropriately when formulating management plans (Sotirov 2017, Gustafsson et al. 2020). Of the three biodiversity indicators we examined, two focus specifically on deadwood, which provides habitat for numerous species across trophic levels (Lassauce et al. 2011, Seibold et al. 2015, Augustynczik and Yousefpour 2019, Härtl and Knoke 2019).

We emphasized deadwood not only because it is a well-documented indicator that is operationalized in forest management decision-making across much of Central Europe, but also because increasing the amount of deadwood can conflict with economic objectives (Müller et al. 2015, Härtl and Knoke 2019). Up to a point, more deadwood supports higher biodiversity, but it also restricts the amount of timber that can be harvested and sold (Härtl et al. 2018). This trade-off can be complex because the biodiversity response depends not only on the quantity of deadwood, but also its location, size, quality, and source species (Gossner et al. 2016, Seibold et al. 2016, Vogel et al. 2020). Developing methods to cost-effectively integrate deadwood into management planning is an active area of research (Doerfler et al. 2017).

Forest management activities also influence arthropod communities, *inter alia* by manipulating the composition of tree communities (Seibold et al. 2019). Saproxylic beetles in particular are dependent on the availability of deadwood and old trees (Seibold et al. 2016). The number of beetle species can grow significantly with incremental increases in the number of available tree species because different trees support different microhabitats (Asbeck et al. 2021) and produce deadwood with different characteristics (Gossner et al. 2016, Andringa et al. 2019, Vogel et al. 2020). This is partly because they decompose at different rates: under Central European conditions, for instance, beech decomposes much faster than Douglas fir or silver fir (Kahl et al. 2017, Vogel et al. 2020). Although forest management guidelines often interpret decomposition rates as a reflection of the relative diversity of the organismal community associated with each tree species, we acknowledge that it can be an imperfect heuristic with some notable counterexamples, e.g. wood-inhabiting fungi (Purahong et al. 2017).

Overall, while biodiversity indicators based primarily on tree species selection likely face some fundamental limitations, the literature already offers several empirically supported starting points. Expanding and improving upon the set of practical indicators capable of leveraging standard inventory data could be a useful direction for future research. In the next subsection, we critically evaluate some potential challenges associated with integrating such indicators into high-level strategic decision-making.

Accounting for biodiversity at the portfolio level

As in any model, our calculations rest on several important simplifying assumptions. Notably, our formulation assumes that the total performance of the portfolio is equivalent to the summed individual performances of each species within it (additivity), each of which scales linearly with the area allocated to it (proportionality). While these assumptions are not necessarily problematic for estimating soil rent, they do require biodiversity indicators to be selected parsimoniously, which matters because indicator selection can be a major source of uncertainty and even systematic error (Kangas et al. 2018). Biodiversity science often focuses on spatial and scalar interactions (Sebald et al. 2021), but for pragmatic reasons forest managers and policymakers often require biodiversity indicators that can be linked directly to the parameters defining typical management alternatives, like species selection or age distribution (Gao et al. 2015, Botequim et al. 2021). For instance, Augustynczik et al. (2020) explore trade-offs between biodiversity and economics under disturbance risk using a Bernstein approximation, but chose a structural biodiversity indicator that does not allow the effects of different tree species allocations on these outcomes to be evaluated.

To select our indicators and estimate their values for each tree species, we relied on past research as described above (Augustynczik and Yousefpour 2019, Härtl and Knoke 2019), but extending the assumptions of additivity and proportionality to these biodiversity indicators deserves scrutiny. For instance, Paul et al. (2020) describe a range of potential functional relationships between biodiversity and economic outcome, including dynamics like species saturation or other feedbacks. Our model does not account for such non-linearities, which is a limitation when considering biodiversity. Capturing non-linearities is a methodological problem (see e.g. Kolo et al. 2020). Non-linearities imply that the decision variables (here the area proportions allocated to six tree species) are not only an outcome of the optimization, but also influence the input information (e.g. the number of saproxylic beetles per deadwood species may be impacted by the amount of deadwood). Such feedback loops push the model toward a non-linear structure. Non-linear optimization problems cannot be solved exactly with standard approaches though, unless one computes all possible combinatorial solution variants (complete enumeration), which is often impossible. A solution could be to optimize the tree species composition (excluding non-linearities) to obtain a specific deadwood amount, which could then be used to recursively update the richness for the deadwood amount obtained and then optimize again. Reiterating this process, we could approach a valid model solution. We think that the integration of such non-linearities could be the topic of future studies. Here, we found it very important to introduce the optimization method as such and show how it could potentially work.

That said, our model can easily accommodate the inclusion of additional indicators beyond the three we examined here. Future research might seek to incorporate indicators based on fungal communities, functional diversity (Thom et al. 2021), or stand structure (Heidrich et al. 2020) and recovery after severe disturbance (Knoke et al. 2022b). Similarly, the treatment of deadwood might be made more balanced by including variables like saproxylic species and decay rate. Incorporating this kind of information could allow our approach to be extended to different harvesting strategies or augmented by integrating simulated stochastic disturbances to explore differences in biodiversity in different successional phases (Hilmers et al. 2018).

While the ecological importance of forest biodiversity has already been frequently studied, the consequences of enhancing the proportions of currently rare tree species for both economic return and biodiversity indicators have hardly been analyzed (Couture et al. 2021). In addition, the potential costs for forest managers for providing biodiversity conservation as an important public good and a desirable tree species portfolio to reduce such costs has so far seldom been on the research agenda (Borges et al. 2014).

Conclusion

Conflicting objectives are common in forest management. Using Pareto frontiers built on multi-objective robust optimization, we generate tree species portfolios representing a spectrum of possible compromises between *biodiversity* and *economic* performance. Our results shed light on debates about the possible expansion of currently rare silver fir and Douglas fir in German forest portfolios as a climate change adaptation measure. We find that portfolios that exclude these species do not achieve better performance on an aggregate biodiversity indicator, but do exhibit reductions in economic robustness. We highlight an inflection point in the trade-off curve at around 25% of the theoretically maximal biodiversity score, beyond which the marginal cost of additional biodiversity improvements increases sharply. Generally, compromising portfolios are more diverse and feature larger shares of hardwoods than a purely economic baseline, suggesting that these solutions could support risk buffering and closer-to-nature forestry paradigms that favor mixed stands with more structural complexity.

This novel approach offers a means of addressing an important gap in Pareto-based environmental management decision support tools: not all combinations of objectives are subject to the same risks. By representing only solutions that are robust to future uncertainty, our method can provide decision-makers with trade-off and opportunity cost information to support minimum guaranteed performance in multifunctional management. It may also provide a basis for calculating biodiversity premia, which might be used to design financial incentives to encourage more widespread adoption of ecologically and economically resilient closer-to-nature management. This study offers a first close-to-practice tree species portfolio for German forests considering the influence of biodiversity on the long-term financial outcome of a forest enterprise under uncertainty.

Acknowledgements

The authors would like to thank Juanita Schmidhammer and Andrew Alvarado for language editing.

Author contributions

Benjamin Gang (Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Validation, Visualization, Writing—original draft, Writing—review & editing), Logan Bingham (Validation, Writing—original draft, Writing—review & editing), Elizabeth Gosling (Methodology, Software, Validation), Thomas Knoke (Conceptualization, Funding acquisition, Methodology, Supervision, Writing—original draft, Writing—review & editing).

Conflict of interest: None declared.

Funding

This research and the Open Access of this publication was funded by the Bavarian State Ministry of Food, Agriculture and Forestry (grant number H011). L.R.B. received support from the European Union's Horizon 2020 research and innovation program under the Marie Sklodowska Curie grant agreement number 956355.

Data availability

The data underlying this article will be shared on reasonable request to the corresponding author.

References

Andringa, JI, Zuo, J, Berg, MP *et al.* 2019 Combining tree species and decay stages to increase invertebrate diversity in dead wood. *For Ecol Manage* **441**, 80–88. https://doi.org/10.1016/j.foreco.2019.03.029.

Arnott, D and Gao, S 2019 Behavioral economics for decision support systems researchers. *Decis Support Syst* **122**, 113063. https://doi.org/10.1016/j.dss.2019.05.003.

Asbeck, T, Sabatini, F, Augustynczik, ALD *et al.* 2021 Biodiversity response to forest management intensity, carbon stocks and net primary production in temperate montane forests. *Sci Rep* **11**, 1625. https://doi.org/10.1038/s41598-020-80499-4.

Augustynczik, ALD, Asbeck, T, Basile, M *et al.* 2020 Reconciling forest profitability and biodiversity conservation under disturbance risk: the role of forest management and salvage logging. *Environ Res Lett* **15**, 0940a3. https://doi.org/10.1088/1748-9326/abad5a.

Augustynczik, ALD and Yousefpour, R 2019 Balancing forest profitability and deadwood maintenance in European commercial forests: a robust optimization approach. *Eur J Forest Res* **138**, 53–64. https://doi.org/10.1007/s10342-018-1153-9.

Augustynczik, ALD, Yousefpour, R and Hanewinkel, M 2018 Multiple uncertainties require a change of conservation practices for saproxylic beetles in managed temperate forests. *Sci Rep* **8**, 14964. https://doi.org/10.1038/s41598-018-33389-9.

Bindewald, A, Miocic, S, Wedler, A *et al.* 2021 Forest inventory-based assessments of the invasion risk of *Pseudotsuga menziesii* (Mirb.) Franco and *Quercus rubra* L. in Germany. *Eur J Forest Res* **140**, 883–899. https://doi.org/10.1007/s10342-021-01373-0.

Borges, JG, Garcia-Gonzalo, J, Bushenkov, V *et al.* 2014 Addressing multicriteria forest management with Pareto frontier methods: an application in Portugal. *For Sci* **60**, 63–72. https://doi.org/10.5849/forsci.12-100.

Botequim, B, Bugalho, MN and Rodrigues, AR 2021 Combining tree species composition and understory coverage indicators with optimization techniques to address concerns with landscape-level biodiversity. *Landarzt* **10**, 126. https://doi.org/10.3390/land10020126.

Brandl, S, Paul, C, Knoke, T *et al.* 2020 The influence of climate and management on survival probability for Germany's most important tree species. *For Ecol Manage* **458**, 117652. https://doi.org/10.1016/j.foreco.2019.117652.

Brändle, M and Brandl, R 2001 Species richness of insects and mites on trees: expanding southwood. *J Anim Ecol* **70**, 491–504. https://doi.org/10.1046/j.1365-2656.2001.00506.x.

Chung, W 2015 Optimizing fuel treatments to reduce wildland fire risk. *Curr Forestry Rep* **1**, 44–51. https://doi.org/10.1007/s40725-015-0005-9.

Couture, S, Cros, M-J and Sabbadin, R 2021 Multi-objective sequential forest management under risk using a Markov decision process-Pareto frontier approach. *Environ Model Assess* **26**, 125–141. https://doi.org/10.1007/s10666-020-09736-4.

Dekker, T, Hess, S, Brouwer, R *et al.* 2016 Decision uncertainty in multi-attribute stated preference studies. *Resour Energy Econ* **43**, 57–73. https://doi.org/10.1016/j.reseneeco.2015.11.002.

Díaz-Yáñez, O, Pukkala, T, Packalen, P *et al.* 2021 Multi-objective forestry increases the production of ecosystem services. *Forestry* **94**, 386–394. https://doi.org/10.1093/forestry/cpaa041.

Dickinson, KL, Brenkert-Smith, H, Madonia, G *et al.* 2020 Risk interdependency, social norms, and wildfire mitigation: a choice experiment. *Nat Hazards* **103**, 1327–1354. https://doi.org/10.1007/s11069-020-04037-1.

Doerfler, I, Müller, J, Gossner, MM *et al.* 2017 Success of a deadwood enrichment strategy in production forests depends on stand type and management intensity. *For Ecol Manage* **400**, 607–620. https://doi.org/10.1016/j.foreco.2017.06.013.

Dragicevic, A, Lobianco, A and Leblois, A 2016 Forest planning and productivity-risk trade-off through the Markowitz mean-variance model. *Forest Policy Econ* **64**, 25–34. https://doi.org/10.1016/j.forpol.2015.12.010.

Dyckhoff, H and Souren, R 2022 Integrating multiple criteria decision analysis and production theory for performance evaluation: framework and review. *Eur J Oper Res* **297**, 795–816. https://doi.org/10.1016/j.ejor.2021.05.046.

Eggers, J, Lundström, J, Snäll, T *et al.* 2022 Balancing wood production and biodiversity in intensively managed boreal forest. *Scand J For Res* **37**, 213–225. https://doi.org/10.1080/02827581.2022.2066170.

Eyvindson, K and Kangas, A 2018 Guidelines for risk management in forest planning—what is risk and when is risk management useful? *Can J For Res* **48**, 309–316. https://doi.org/10.1139/cjfr-2017-0251.

Farley, J and Kish, K 2021 Ecological economics: the next 30 years. *Ecol Econ* **190**, 107211. https://doi.org/10.1016/j.ecolecon.2021.107211.

Federal Ministry of Food and Agriculture (BMEL). *The Forests in Germany. Selected Results for the Third National Forest Inventory*. BMEL, Berlin, 2014.

França, LCDJ, Júnior, FWA, Jarochinski e Silva, CS *et al.* 2022 Forest landscape planning and management: a state-of-the-art review. *Trees, Forests and People* **8**, 100275. https://doi.org/10.1016/j.tfp.2022.100275.

Friedrich, S, Hilmers, T, Chreptun, C *et al.* 2021 The cost of risk management and multifunctionality in forestry: a simulation approach for a case study area in Southeast Germany. *Eur J Forest Res* **8**, 363.

Gao, T, Nielsen, AB and Hedblom, M 2015 Reviewing the strength of evidence of biodiversity indicators for forest ecosystems in Europe. *Ecol Indic* **57**, 420–434. https://doi.org/10.1016/j.ecolind.2015.05.028.

Gosling, E, Knoke, T, Reith, E *et al.* 2021 Which socio-economic conditions drive the selection of agroforestry at the forest frontier? *Environ Manag* **67**, 1119–1136. https://doi.org/10.1007/s00267-021-01439-0.

Goßner, M and Ammer, U 2006 The effects of Douglas fir on tree-specific arthropod communities in mixed species stands with European beech and Norway spruce. *Eur J Forest Res* **125**, 221–235. https://doi.org/10.1007/s10342-006-0113-y.

Gossner, MM, Wende, B, Levick, S *et al.* 2016 Deadwood enrichment in European forests – which tree species should be used to promote saproxylic beetle diversity? *Biol Conserv* **201**, 92–102. https://doi.org/10.1016/j.biocon.2016.06.032.

Greco, S, Ishizaka, A, Tasiou, M *et al.* 2019 On the methodological framework of composite indices: a review of the issues of weighting, aggregation, and robustness. *Soc Indic Res* **141**, 61–94. https://doi.org/10.1007/s11205-017-1832-9.

Gustafsson, L, Bauhus, J, Asbeck, T *et al.* 2020 Retention as an integrated biodiversity conservation approach for continuous-cover forestry in Europe. *Ambio* **49**, 85–97. https://doi.org/10.1007/s13280-019-01190-1.

Hanewinkel, M, Hummel, S and Cullmann, DA 2010 Modelling and economic evaluation of forest biome shifts under climate change in Southwest Germany. *For Ecol Manage* **259**, 710–719. https://doi.org/10.1016/j.foreco.2009.08.021.

Hanewinkel M, Lessa Derci Augustynczik A, Yousefpour R. Climate-smart forestry case study: Germany. In Hetemäki L, Kangas J and Peltola H (eds). *Forest Bioeconomy and Climate Change. Managing Forest Ecosystems*. 1st edn. Springer, Cham, vol **42**, pp. 197–209, 2022. https://doi.org/10.1007/978-3-030-99206-4_12.

Härtl, F and Knoke, T 2019 Coarse woody debris management with ambiguous chance constrained robust optimization. *Forests* **10**, 504. https://doi.org/10.3390/f10060504.

Härtl, FH, Langhammer, P and Knoke, T 2018 Strategien zur Minimierung von Opportunitätskosten der Totholzbereitstellung. *Schweizerische Zeitschrift fur Forstwesen* **169**, 9–17. https://doi.org/10.3188/szf.2018.0009.

Heidrich, L, Bae, S, Levick, S *et al.* 2020 Heterogeneity-diversity relationships differ between and within trophic levels in temperate forests. *Nat Ecol Evol* **4**, 1204–1212. https://doi.org/10.1038/s41559-020-1245-z.

Herbert, C, Haya, BK, Stephens, SL *et al.* 2022 Managing nature-based solutions in fire-prone ecosystems: competing management objectives in California forests evaluated at a landscape scale. *Front For Glob Change* **5**, 1–16. https://doi.org/10.3389/ffgc.2022.957189.

Hilmers, T, Friess, N, Bässler, C *et al.* 2018 Biodiversity along temperate forest succession. *J Appl Ecol* **55**, 2756–2766. https://doi.org/10.1111/1365-2664.13238.

Jarisch, I, Bödeker, K, Bingham, LR *et al.* 2022 The influence of discounting ecosystem services in robust multi-objective optimization—an application to a forestry-avocado land-use portfolio. *For Policy Econ* **141**, 102761. https://doi.org/10.1016/j.forpol.2022.102761.

Kahl, T, Arnstadt, T, Baber, K *et al.* 2017 Wood decay rates of 13 temperate tree species in relation to wood properties, enzyme activities and organismic diversities. *For Ecol Manage* **391**, 86–95. https://doi.org/10.1016/j.foreco.2017.02.012.

Kaim, A, Bartkowski, B, Lienhoop, N *et al.* 2021 Combining biophysical optimization with economic preference analysis for agricultural land-use allocation. *E&S* **26**. https://doi.org/10.5751/ES-12116-260109.

Kangas, A, Korhonen, KT, Packalen, T *et al.* 2018 Sources and types of uncertainties in the information on forest-related ecosystem services. *For Ecol Manage* **427**, 7–16. https://doi.org/10.1016/j.foreco.2018.05.056.

Kindu, M, Le Mai, TN, Bingham, LR *et al.* 2022 Auctioning approaches for ecosystem services—evidence and applications. *Sci Total Environ* **853**, 158534. https://doi.org/10.1016/j.scitotenv.2022.158534.

Knoke T, Messerer K and Paul C. 2017 The role of economic diversification in forest ecosystem management. *Curr Forestry Rep* **3**, 93–106.

Knoke, T, Gosling, E and Reith, E 2022a Understanding and modelling the ambiguous impact of off-farm income on tropical deforestation. *J Land Use Sci* **17**, 658–676. https://doi.org/10.1080/1747423X.2022.2146220.

Knoke, T, Kindu, M, Jarisch, I *et al.* 2020 How considering multiple criteria, uncertainty scenarios and biological interactions may influence the optimal silvicultural strategy for a mixed forest. *Forest Policy Econ* **118**, 102239. https://doi.org/10.1016/j.forpol.2020.102239.

Knoke, T, Messerer, K and Paul, C 2017 The role of economic diversification in forest ecosystem management. *Curr For Rep* **3**, 93–106. https://doi.org/10.1007/s40725-017-0054-3.

Knoke, T, Paul, C, Gosling, E *et al.* 2022b Assessing the economic resilience of different management systems to severe forest disturbance. *Environ Resour Econ* **84**, 343–381.

Knoke, T, Paul, C, Hildebrandt, P *et al.* 2016 Compositional diversity of rehabilitated tropical lands supports multiple ecosystem services and buffers uncertainties. *Nat Commun* **7**, 11877. https://doi.org/10.1038/ncomms11877.

Kolo, H, Kindu, M and Knoke, T 2020 Optimizing forest management for timber production, carbon sequestration and groundwater recharge. *Ecosyst Serv* **44**, 101147. https://doi.org/10.1016/j.ecoser.2020.101147.

Lassauce, A, Paillet, Y, Jactel, H *et al.* 2011 Deadwood as a surrogate for forest biodiversity: meta-analysis of correlations between deadwood volume and species richness of saproxylic organisms. *Ecol Indic* **11**, 1027–1039. https://doi.org/10.1016/j.ecolind.2011.02.004.

Louviere, J and Meyer, RJ 2017 Formal choice models of informal choices. What choice modeling research can (and can't) learn from behavioral theory. *Rev Mark* **4**, 3–32.

Luyssaert, S, Marie, G, Valade, A *et al.* 2018 Trade-offs in using European forests to meet climate objectives. *Nature* **562**, 259–262. https://doi.org/10.1038/s41586-018-0577-1.

Marques, S, Bushenkov, V, Lotov, A *et al.* 2021 Building Pareto frontiers for ecosystem services tradeoff analysis in forest management planning integer programs. *Forests* **12**, 1244. https://doi.org/10.3390/f12091244.

Marto, M, Reynolds, K, Borges, J *et al.* 2018 Combining decision support approaches for optimizing the selection of bundles of ecosystem services. *Forests* **9**, 438. https://doi.org/10.3390/f9070438.

Mason AJ. OpenSolver—an open source add-in to solve linear and integer progammes in Excel. In: Klatte D, Lüthi H-J and Schmedders K (eds). *Operations Research Proceedings 2011*. Springer, Berlin Heidelberg, pp. 401–406, 2012. https://doi.org/10.1007/978-3-642-29210-1_64.

Mazziotta, A, Podkopaev, D, Triviño, M *et al.* 2017 Quantifying and resolving conservation conflicts in forest landscapes via multiobjective optimization. *Silva Fenn* **51**, 1–19. https://doi.org/10.14214/sf.1778.

Messerer, K, Pretzsch, H and Knoke, T 2017 A non-stochastic portfolio model for optimizing the transformation of an even-aged forest stand to continuous cover forestry when information about return fluctuation is incomplete. *Ann For Sci* **74**, 2. https://doi.org/10.1007/s13595-017-0643-0.

Müller, J, Wende, B, Strobl, C *et al.* 2015 Forest management and regional tree composition drive the host preference of saproxylic beetle communities. *J Appl Ecol* **52**, 753–762. https://doi.org/10.1111/1365-2664.12421.

Paul, C, Nick, H, Sebastian, TM *et al.* 2020 On the functional relationship between biodiversity and economic value. *Sci Adv* **6**, eaax7712. https://doi.org/10.1126/sciadv.aax7712.

Paul, C, Reith, E, Salecker, J *et al.* 2019 How integrated ecological-economic modelling can inform landscape pattern in forest agroecosystems. *Curr Landsc Ecol Rep* **4**, 125–138. https://doi.org/10.1007/s40823-019-00046-4.

Pötzelsberger, E, Spiecker, H, Neophytou, C *et al.* 2020 Growing non-native trees in European forests brings benefits and opportunities but also has its risks and limits. *Curr Forestry Rep* **6**, 339–353. https://doi.org/10.1007/s40725-020-00129-0.

Pretzsch, H, Biber, P and Ďurský, J. 2002 The single tree-based stand simulator SILVA: construction application and evaluation. *For Ecol Manage* **162**, 3–21.

Přívětivý, T, Adam, D and Vrška, T 2018 Decay dynamics of *Abies alba* and *Picea abies* deadwood in relation to environmental conditions. *For Ecol Manage* **427**, 250–259. https://doi.org/10.1016/j.foreco.2018.06.008.

Purahong, W, Wubet, T, Krüger, D *et al.* 2017 Molecular evidence strongly supports deadwood-inhabiting fungi exhibiting unexpected tree species preferences in temperate forests. *ISME J* **12**, 289–295. https://doi.org/10.1038/ismej.2017.177.

Rönnqvist, M, D'Amours, S, Weintraub, A *et al.* 2015 Operations research challenges in forestry: 33 open problems. *Ann Oper Res* **232**, 11–40. https://doi.org/10.1007/s10479-015-1907-4.

Sebald, J, Thrippleton, T, Rammer, W *et al.* 2021 Mixing tree species at different spatial scales: the effect of alpha, beta and gamma diversity on disturbance impacts under climate change. *J Appl Ecol* **58**, 1749–1763. https://doi.org/10.1111/1365-2664.13912.

Seibold, S, Bässler, C, Brandl, R *et al.* 2016 Microclimate and habitat heterogeneity as the major drivers of beetle diversity in dead wood. *J Appl Ecol* **53**, 934–943. https://doi.org/10.1111/1365-2664.12607.

Seibold, S, Bässler, C, Brandl, R *et al.* 2015 Experimental studies of dead-wood biodiversity—a review identifying global gaps in knowledge. *Biol Conserv* **191**, 139–149. https://doi.org/10.1016/j.biocon.2015.06.006.

Seibold, S, Gossner, MM, Simons, NK *et al.* 2019 Arthropod decline in grasslands and forests is associated with landscape-level drivers. *Nature* **574**, 671–674. https://doi.org/10.1038/s41586-019-1684-3.

Sierra-Altamiranda, A, Charkhgard, H, Eaton, M *et al.* 2020 Spatial conservation planning under uncertainty using modern portfolio theory and Nash bargaining solution. *Ecol Model* **423**, 109016. https://doi.org/10.1016/j.ecolmodel.2020.109016.

Sotirov, M (ed) 2017 *Natura 2000 and Forests: Assessing the State of Implementation and Effectiveness*. European Forest Institute, Joensuu, Finland, p. 143.

Sousa-Silva, R, Verbist, B, Lomba, Â *et al.* 2018 Adapting forest management to climate change in Europe: linking perceptions to adaptive responses. *For Policy Econ* **90**, 22–30. https://doi.org/10.1016/j.forpol.2018.01.004.

Temperli, C, Blattert, C, Stadelmann, G *et al.* 2020 Trade-offs between ecosystem service provision and the predisposition to disturbances: a NFI-based scenario analysis. *For Ecosyst* **7**, 1–17. https://doi.org/10.1186/s40663-020-00236-1.

Thom, D, Taylor, AR, Seidl, R *et al.* 2021 Forest structure, not climate, is the primary driver of functional diversity in northeastern North America. *Sci Total Environ* **762**, 143070. https://doi.org/10.1016/j.scitotenv.2020.143070.

Thurm, EA, Hernandez, L, Baltensweiler, A *et al.* 2018 Alternative tree species under climate warming in managed European forests. *For Ecol Manage* **430**, 485–497. https://doi.org/10.1016/j.foreco.2018.08.028.

Uhde, B, Heinrichs, S, Stiehl, CR *et al.* 2017 Bringing ecosystem services into forest planning—can we optimize the composition of Chilean forests based on expert knowledge? *For Ecol Manage* **404**, 126–140. https://doi.org/10.1016/j.foreco.2017.08.021.

Vitali, V, Büntgen, U and Bauhus, J 2017 Silver fir and Douglas fir are more tolerant to extreme droughts than Norway spruce in south-western Germany. *Glob Chang Biol* **23**, 5108–5119. https://doi.org/10.1111/gcb.13774.

Vitali, V, Forrester, DI and Bauhus, J 2018 Know your neighbours: drought response of Norway spruce, silver fir and Douglas fir in mixed forests depends on species identity and diversity of tree neighbourhoods. *Ecosystems* **21**, 1215–1229. https://doi.org/10.1007/s10021-017-0214-0.

Vogel, S, Bussler, H, Finnberg, S *et al.* 2020 Diversity and conservation of saproxylic beetles in 42 European tree species: an experimental approach using early successional stages of branches. *Insect Conserv Divers* **18**, 1.

West, TAP, Salekin, S, Melia, N *et al.* 2021 Diversification of forestry portfolios for climate change and market risk mitigation. *J Environ Manage* **289**, 112482. https://doi.org/10.1016/j.jenvman.2021.112482.

Wolgemuth, T, Gossner, M and Rigling, A 2021 Chancen und Risiken der Douglasie im Waldbau. *Schweizerische Zeitschrift fur Forstwesen* **172**, 62–65. https://doi.org/10.3188/szf.2021.0062.

Yousefpour, R and Hanewinkel, M 2016 Climate change and decision-making under uncertainty. *Curr Forestry Rep* **2**, 143–149. https://doi.org/10.1007/s40725-016-0035-y.

Yousefpour, R, Jacobsen, JB, Thorsen, BJ *et al.* 2012 A review of decision-making approaches to handle uncertainty and risk in adaptive forest management under climate change. *Ann For Sci* **69**, 1–15. https://doi.org/10.1007/s13595-011-0153-4.