Interactive decision support and trade-off analysis for sustainable forest landscape planning under deep uncertainty

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Abstract

Sustainable environmental management often involves long-term time horizons, multiple conflicting objectives, and by nature, is affected by different sources of uncertainty. Many sources of uncertainty, such as climate change or government policies, cannot be addressed using probabilistic models, and, therefore, they can be seen to contain deep uncertainty. In this setting, the variety of possible future states is represented as a set of scenarios lacking any information about the likelihood of occurring. Integrating deep uncertainty into multiobjective decision support increases complexity, calling for the elaboration of appropriate methods and tools. This paper proposes a novel interactive multi-scenario multiobjective approach to support decision-making and trade-off analysis in sustainable forest landscape planning under multiple sources of uncertainty. It includes new preference simulation models aimed at reducing the decision-maker's cognitive load and supporting the preference elicitation process. The proposed approach is applied in a case study of long-term forest landscape planning with four sustainability objectives in twelve scenarios and a forestry expert as the decision-maker. The approach is demonstrated to be efficient in exploring trade-offs in different scenarios, helping the expert gain deep insights into the problem, understand the consequences of alternative strategies, and find the most preferred robust strategy.

Keywords: Forest management; Climate change; Multiobjective optimization; Scenario planning; Partially known preferences

1 Introduction

We study problems of sustainable environmental management, in particular forest landscape planning, with a long-term time horizon and multiple conflicting objectives (such as timber revenue, carbon storage and biodiversity). Conflicts between objectives imply that a solution does not exist which would be optimal with respect to all objectives simultaneously. Instead, the solution must be sought among the set of so-called *Pareto optimal solutions* with various trade-offs between the objectives that brings the requirement of a domain expert (e.g., the manager or the decision-maker (DM)) to choose the final solution among various compromises. This set is unknown a priori, and each individual solution needs to be generated using mathematical methods. Therefore, the DM needs additional support to study these trade-offs and find the best balance between conflicting objectives. This typically is based on his/her preferences. Multiobjective optimization methods have been developed to provide this kind of support to DMs over the years in a wide range of real-life applications, including various aspects of forest planning. Some examples of decision support methods and case studies in forest planning can be found in Kangas et al. (2001), Eyvindson et al. (2018), Marques et al. (2021a), and Marques et al. (2021b) (see also references therein). Papers Mönkkönen et al. (2014), Kangas et al. (2015), and Triviño et al. (2017) develop various multiobjective models of forest landscape planning for analyzing trade-offs between different objectives. Some examples of mathematical methods for solving multiobjective problems of forest management can be found in Tóth and McDill (2009) and references.

The DM may provide preferences before, after, or during the solution process. These three ways of providing preferences give raise to three types of multiobjective optimization methods: *a priori*, *a posteriori*, and *interactive*, respectively (Hwang and Masud, 1979; Buchanan, 1986; Miettinen, 1999). The effectiveness of *a priori* methods highly depends on the level of qualification and prior knowledge of the DM about the problem. Otherwise, the preferences provided before the solution process may be overly optimistic or pessimistic. In contrast, *a posteriori* methods aim at generating a large, diverse set representing Pareto optimal solutions. This is a barrier when applying to computationally complex problems and gets cognitively more and more challenging for the DM as the number of objectives grows. *Interactive* methods aim at, to some extent, avoiding the disadvantages mentioned above. They involve an iterative solutions process that allows the DM to gain insight into the problem, explore trade-offs between objectives, and learn about the feasibility of preferences. Interactive methods save computation resources and reduce cognitive load by focusing only on solutions that are interesting to the DM. Interactive methods have proved their potential for multiobjective decision support in different environmental and forest management applications (e.g., Tecle et al., 1994; Hartikainen et al., 2015, 2016; Eyvindson et al., 2018; Saccani et al., 2020).

Like many real-life problems, environmental management problems such as forest planning face different sources of uncertainty due to the unknown future states of the world, e.g., climate and environmental change, production demand, government policy changes, and natural hazards. Due to the lack of models and/or insufficient data, such types of uncertainty cannot necessarily be framed in probabilistic terms or even described parametrically. This situation is often referred to as *deep uncertainty*, i.e., when researchers do not know or cannot agree upon some aspects of the systems and/or outcomes such as their probability distributions, boundaries, or related preferences (Lempert et al., 2003; Walker et al., 2013). In such cases, however, the future states of the world can be represented as *scenarios*. More specifically, one can enumerate plausible future states of the world and corresponding outcomes of planning but cannot define their occurrence probabilities or ranking with enough accuracy because of the complexity and the lack of evidence (Lempert et al., 2006; Shavazipour and Stewart, 2021).

Deep uncertainties, in particular those related to climate change, significantly affect the performance of forest management strategies. Thus, taking them into account is vital for robust and sustainable forest planning (Seidl et al., 2017; Augustynczik and Yousefpour, 2019). It is worth noting that the ecosystem management activities need to be started decades before the realization of the uncertain factors (Spittlehouse and Stewart, 2003; Millar et al., 2007; Petr et al., 2019). This necessitates the integration of deep uncertainty aspects into the planning process, bringing significant challenges to environmental DMs. Scenario planning has been widely applied in handling uncertainty in decision-making (see, e.g., Van der Heijden (1996)). It provides a framework for thinking, planning, and concrete discussions of uncertainty (Durbach and Stewart, 2012). Since planning outcomes may be sensitive to the consequences of uncertainty, one crucial aspect of decision-making under uncertainty is identifying decisions that perform relatively well in a broader range of scenarios (called robust decisions) (Lempert et al., 2006).

The multiobjective nature of environmental planning problems combined with their dependence on deep uncertainty brings more complexity (and introduces an additional dimension) to the solution process, making the DM's task cognitively more demanding (Shavazipour et al., 2021b). Recently, different approaches integrated multiobjective optimization and scenario planning to cope with deep uncertainty and help the DM analyze trade-offs between objectives under various scenarios and find the most preferred robust solution (e.g., Watson and Kasprzyk (2017); Eker and Kwakkel (2018); Shavazipour and Stewart (2021); Shavazipour et al. (2021a)), forming a class of decision problems called *multi-scenario multiobjective optimization*. The issue of cognitive complexity needs to be addressed by creating easy-to-understand preference handling techniques and graphical visualizations. Existing decision support tools in forest management rarely consider both multiple objectives and deep uncertainty aspects (Yousefpour and Hanewinkel, 2016; Radke et al., 2017, 2020; Hörl et al., 2020). This study is an effort to fill this vital gap in the literature.

In this paper, we propose a novel interactive multi-scenario multiobjective optimization approach as a decision support tool for environmental planning problems under deep uncertainty and in particular, sustainable forest management. Our decision support tool includes advanced visualization techniques recently developed for multi-scenario multiobjective optimization problems (Shavazipour et al., 2021b) to analyze trade-offs between objectives in various scenarios. To the best of our knowledge, this is the first study of interactive environmental decision support combining multiobjective trade-offs exploration with multi-scenario considerations, such as optimality/feasibility in any given scenario and robustness over the set of future scenarios.

As mentioned earlier, interactive methods for solving multiobjective problems rely on DM's preferences. Different methods enable a DM to express preferences in different ways (Miettinen et al., 2016). We concentrate on the class of methods which utilize preference information provided as *reference points*. A *reference point* is a vector composed of so-called *aspiration levels*, which are desirable values of the objective functions. This type of preference information is in line with the concept of "satisficing" (Simon (1956); Wierzbicki (1982)), which is regarded as cognitively undemanding for the DM. Reference point-based methods have been widely used in practice, including environmental and forest management (e.g., Krcmar-Nozic et al. (1998); Eyvindson et al. (2018); Shavazipour et al. (2021a)).

In multi-scenario multiobjective optimization problems, each objective in each scenario is represented by an individual objective function. Thus, the DM is expected to provide aspiration levels for all combinations of objectives and scenarios (Shavazipour et al., 2020; Shavazipour and Stewart, 2021). This can impose a high cognitive load on the DM, even for problems of moderate sizes. For example, for a problem with 3 to 5 objectives and 4 to 7 scenarios, the required number of aspiration levels is from 12 to 35. It is far beyond the "magical number" 7 ± 2 proposed by Miller (1956) as the estimation of short-term memory capacity. Thus, setting all required aspiration levels can be difficult or beyond human capabilities. In practice, we cannot expect the preferences for all objectives in all scenarios to be available from the DM and, thus, in many cases, we have to deal with incomplete preferences. Therefore, our approach to interactive decision support allows expressing partial preference information and includes a tool to simulate missing preferences of the DM.

To illustrate our novel approach, we consider a large-scale forest landscape management problem with tens of thousands of forest stands and a 50-year planning horizon. The problem is formulated as a multi-scenario multiobjective mixed-integer optimization problem with four objective functions: (i) maximizing timber harvest revenue as net present value (NPV), (ii) maximizing carbon storage, (iii) maximizing deadwood, and (iv) maximizing a combined index of species habitat availability. The formulation includes 12 scenarios based on three different sources of deep uncertainty: (a) climate change, (b) forest thinning subsidies, and (c) compensations for forest landscape conservation, that construct a 48-objective optimization model to be solved. We solve this complex, large-scale problem utilizing the proposed interactive multi-scenario multiobjective approach guided by a forestry expert DM. We analyze trade-offs between objectives under various scenarios with the help of advanced visualizations.

The rest of this paper is structured as follows. Section 2 contains a concise statement of multi-scenario multiobjective optimization problems and related definitions, followed by the proposed preference simulation method, the proposed interactive multi-scenario multiobjective approach, and the visualizations utilized for trade-off analysis. The detailed description and problem formulation of the case study of forest landscape planning can be found in Section 3. In Section 4, we demonstrate our experiment of applying the proposed approach with a DM in the case study and the relevant trade-off analysis. Finally, after further discussions in Section 5, we conclude in Section 6.

2 Methodology

2.1 Multi-scenario multiobjective optimization

A multi-scenario multiobjective optimization problem can be formulated as follows (Shavazipour et al., 2021a):

$$\begin{aligned} &\text{minimize} \quad \{f_{1t}(\mathbf{x}), \ldots, f_{kt}(\mathbf{x})\}, \quad t = 1, \ldots, s, \\ &\text{subject to} \quad \mathbf{x} \in S \subseteq \mathbb{R}^n, \end{aligned} \tag{1}$$

where s is the number of scenarios; k is the number of objective functions, and we assume that the number of objectives is the same in all scenarios; f_{it} is the objective function defined in scenario t; $\mathbf{x} = (x_1, \ldots, x_n)^T$ is a feasible solution represented by a vector of decision variables, and $S \subseteq \mathbb{R}^n$ is the set of feasible solutions in the so called *decision space* $\mathbb{R}^n$.

Given a feasible solution $\mathbf{x}$ and scenario $t \in \{1, \ldots, s\}$, we introduce the *objective vector* $\mathbf{z}_t = (f_{1t}(\mathbf{x}), \ldots, f_{kt}(\mathbf{x}))^T$ as the image of a solution $\mathbf{x}$ under the conditions of scenario t in the *objective space* $\mathbb{R}^k$. A feasible solution (decision vector) $\mathbf{x} \in S$ is called *Pareto optimal* if there does not exist another feasible solution with a smaller value of at least one objective function in one scenario and no greater values of any objective functions in any scenarios.

We introduce a so-called *ideal* vector $\mathbf{z}^{ideal}$ with components z_{it}^{ideal}, $i = 1, \ldots, k$, $t = 1, \ldots, s$ and a *nadir* vector $\mathbf{z}^{nadir}$ with components z_{it}^{nadir}, $i = 1, \ldots, k$, $t = 1, \ldots, s$ composed, respectively, of the best and the worst values of the individual objective functions among the set of Pareto optimal solutions. Ideal values can be directly computed by solving the corresponding single-objective single-scenario optimization problems separately for each objective in each scenario. Nadir values are much more difficult to obtain, therefore they are usually approximated (see, e.g., Miettinen (1999)). Without loss of generality, we assume

$$z_{it}^{ideal} < z_{it}^{nadir}, \ i = 1, \ldots, k, \ t = 1, \ldots, s,$$

since the equality between ideal and nadir values for some i and t would mean that the i-th objective function in scenario t is constant for all Pareto optimal solutions, and therefore it can be excluded from the consideration. For any scenario t, we also introduce ideal and nadir vectors in the objective space that are composed of the corresponding values in this scenario, respectively: $\mathbf{z}_t^{ideal} = \left(z_{1t}^{ideal}, z_{2t}^{ideal}, \ldots, z_{kt}^{ideal}\right)$ and $\mathbf{z}_t^{nadir} = \left(z_{1t}^{nadir}, z_{2t}^{nadir}, \ldots, z_{kt}^{nadir}\right)$.

One way of deriving solutions to multiobjective optimization problems is to use a so-called *scalarizing function* to transform the multiobjective problem into a single-objective problem incorporating the DM's preferences (see, e.g., Miettinen (1999); Miettinen and Mäkelä (2002); Ruiz et al. (2009)). An extended version of a so-called achievement scalarizing function (Wierzbicki, 1986) has been recently introduced to solve multi-scenario multiobjective optimization problems (Shavazipour et al., 2020, 2021a). In this paper, we use the multi-scenario version of an achievement scalarizing function formulated by Shavazipour et al. (2021a) as follows:

$$\begin{aligned} &\text{minimize} \quad \max_{i=1,\ldots,k;t=1,\ldots,s} [w_{it}(f_{it}(\mathbf{x}) - \bar{z}_{it})] + \epsilon \sum_{i=1}^{k} \sum_{t=1}^{s} w_{it}(f_{it}(\mathbf{x}) - \bar{z}_{it}) \\ &\text{subject to} \quad \mathbf{x} \in S, \end{aligned} \tag{2}$$

where $\bar{z}_{it}$ with $z_{it}^{ideal} \leq \bar{z}_{it} \leq z_{it}^{nadir}$, is an *aspiration level* representing a DM's preferences in terms of a desirable value for the i-th objective function under the t-th scenario, and w_{it} is the corresponding weight that can be used, e.g., for normalization purposes. The augmentation term $\epsilon \sum_{i=1}^{k} \sum_{t=1}^{s} w_{it}(f_{it}(\mathbf{x}) - \bar{z}_{it})$ guarantees that the solution to (2) is Pareto optimal, where ϵ is a small positive scalar (for details of the augmentation term, see, e.g., Miettinen (1999)).

A vector including aspiration levels for all objectives and all scenarios is called a *reference point*. By solving (2) with different reference points, the DM can obtain different Pareto optimal solutions, although sometimes the same Pareto optimal solution may be associated with multiple reference points. A simple interactive multiobjective optimization method based on this concept can be described as follows:

Step 0. Initialization of the method. Present information about the ideal and nadir vectors to the DM.

Step 1. Ask the DM to specify preference information as a reference point.

Step 2. Derive a Pareto optimal solution by solving (2) and present it to the DM.

Step 3. Ask the DM if this or one of the previously derived solutions is satisfactory as a final solution to the problem. If yes, stop; otherwise, go to Step 1.

2.2 Simulation of incomplete preferences

If we apply the simple interactive method presented in the previous subsection directly, the DM must specify aspiration levels for all objectives and scenarios. In order to reduce the cognitive load of expressing preferences in all scenarios, we allow the DM to set aspiration levels only for some scenarios, and then we fill in missing information by simulating the DM's preferences. Assume that the DM has provided aspiration levels $\overline{z}_{it}$ for all k objective functions, but only in q ($q < s$) scenarios (without loss of generality, we assume that these q scenarios are ordered as the first q scenarios—i.e., $\{1, 2, \ldots, q, q+1, \ldots, s\}$), so, here, $t = 1, \ldots, q$. The main idea of simulating the unknown preferences (the aspiration levels for the remaining $s-q$ scenarios) is to analyze the relationships between the available preference information and the ideal and nadir vectors. These relationships are represented in terms of so-called *distance-based ratios* defined below.

For each scenario $t,\ t = 1, \ldots, s$, and objective $i,\ i = 1, \ldots, k$, we define a distance-based ratio γ_i^t based on the distances between the aspiration level and the corresponding ideal and nadir values:

$$\gamma_i^t = \frac{\overline{z}_{it} - z_{it}^{ideal}}{z_{it}^{nadir} - z_{it}^{ideal}}. \tag{3}$$

It is easy to see that $0 \leq \gamma_i^t \leq 1$.

For each scenario $t,\ t = q+1, \ldots, s$, and each objective function $i,\ i = 1, \ldots, k$, we calculate q candidates for aspiration levels based on the ratios obtained for the first q scenarios:

$$g_{it}^u = z_{it}^{ideal} + \gamma_i^u (z_{it}^{nadir} - z_{it}^{ideal}),\ u = 1, \ldots, q.$$

Thus, we obtain q candidate vectors in the objective space for the t-th scenario: $\mathbf{g}_t^u = (g_{1t}^u, \ldots,\ g_{kt}^u)\,,\ u = 1, \ldots, q$.

Let us denote an estimation of the vector of aspiration levels in scenario t by $\tilde{\mathbf{z}}_t = (\tilde{z}_{1t}, \ldots, \tilde{z}_{kt})$. In order to derive this estimation of a reference point, we limit the search area in the objective space to the convex hull of those q candidate vectors. Figure 1 shows an example of the estimation process in case of a bi-objective problem ($k = 2$). The convex hull of four candidate vectors is outlined by blue lines; the area between the ideal and the nadir vectors is outlined by red dashed lines.

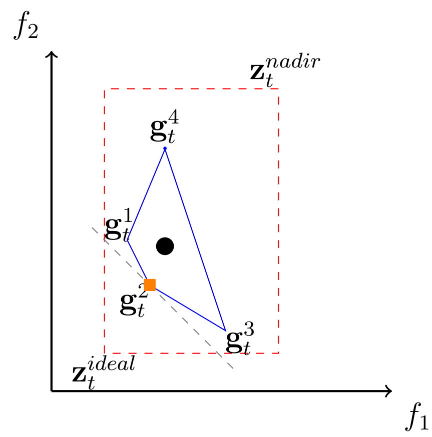

Figure 1: An example of estimating aspiration levels based on four candidates and the convex hull in a bi-objective problem including the idealistic ('■') and moderate ('●') simulated reference points.

We consider two styles of setting preference by a DM, namely *moderate* and *idealistic*, and for each style, propose an optimization model to estimate the unknown preferences. If the DM's style is closer to *moderate*, (s)he may avoid the extremes and cautiously choose a vector in the center of the convex hull (e.g., the vector minimizing the sum of distances to all q candidates). This vector (represented by '●' in Figure 1) can be found by solving the following optimization problem:

$$
\begin{aligned}
&\text{minimize} && \textstyle\sum_{u=1}^{q} \sum_{i=1}^{k} |\tilde{z}_{it} - g_{it}^u| && \\
&\text{subject to} && \tilde{z}_{it} \geq \textstyle\sum_{u=1}^{q} \lambda_u g_{it}^u, && i = 1, \ldots, k \\
& && \textstyle\sum_{u=1}^{q} \lambda_u = 1, && \\
& && \lambda_u \geq 0, && u = 1, \ldots, q.
\end{aligned}
\tag{4}
$$

where $|.|$ returns the absolute value.

To estimate all the unknown aspiration levels, problem (4) needs to be solved for each of $(s-q)$ scenarios. Note that problem (4) is not computationally complex and can be solved very fast. Solving all $(s-q)$ problems could be done in seconds even for a large number of scenarios. Also, problem (4) is always feasible and bounded (see Appendix B for a mathematical proof). So, by using this model, we are always able to find simulated preferences. If the objective functions in the original problem have different scales, model (4) should be normalized, e.g., by replacing the objective function by $\sum_{u=1}^{q}\sum_{i=1}^{k}\frac{|\tilde{z}_{it}-g_{it}^{u}|}{z_{it}^{nadir}-z_{it}^{ideal}}$.

If the DM's style is closer to idealistic, e.g., (s)he has high expectations, the vector of aspiration levels can be estimated as the point of the convex hull which is closest to the ideal vector. In the case of l_1 distance, it is equivalent to the candidate vector which is closest to the ideal vector:

$$\begin{aligned} &\text{minimize} \quad \textstyle\sum_{i=1}^{k}|\tilde{z}_{it}-z_{it}^{ideal}| \\ &\text{subject to} \quad u=1,\ldots,q. \end{aligned} \tag{5}$$

The '■' point in Figure 1 represents the idealistic choice. As above, the model should be normalized if there are objective functions with different scales.

2.3 The proposed approach for multi-scenario multiobjective decision support

We incorporate the method of simulating incomplete preferences with the interactive multiobjective optimization method described in Subsection 2.1. The resulting approach for multi-scenario multiobjective decision support is presented in Figure 2, while the steps are described in Algorithm 1.

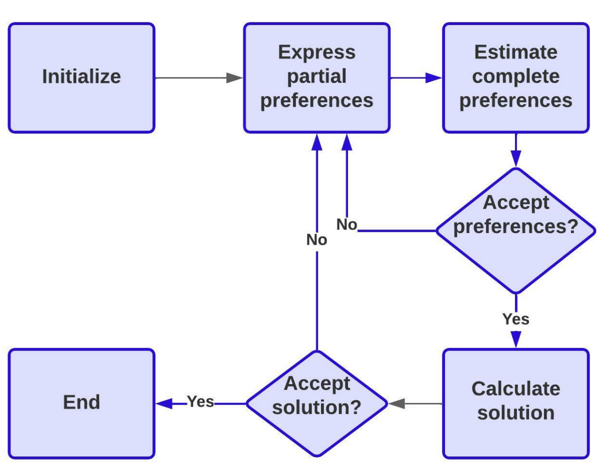

Figure 2: The general flowchart of the proposed interactive approach for multi-scenario multiobjective decision support.

Algorithm 1. The steps of multi-scenario multiobjective decision support approach

1. Initialization. Calculate and present to the DM the ideal and nadir values for all $k \times s$ combinations of objectives and scenarios (as described in subsection 2.1).
2. Ask the DM to specify preferences in one of the following two ways:
   (a) Provide aspiration levels for all k objectives in a freely chosen non-empty subset of scenarios;
   (b) (From second iteration onward) Update aspiration levels, obtained from the previous iteration, for all objectives under all scenarios. The update may include changing aspiration levels and/or removing aspiration levels for a chosen subset of scenarios.
3. Estimate missing preference information if incomplete, as described in Subsection 2.2.
4. If the preference information has been estimated in the previous step and if the DM wishes to review it, show it to the DM. If the DM is not satisfied with the estimation result, go to step 2.
5. Derive a Pareto optimal solution corresponding to the DM's preferences by solving problem (2), and present this solution to the DM.
6. If the DM is not ready to accept the presented solution as the final solution to the problem, go to step 2.
7. Stop. The Pareto optimal solution derived in Step 5 is the final solution to the problem.

2.4 Visual support for trade-off analysis

A scenario-based empirical attainment function (SB-EAF) has been proposed by Shavazipour et al. (2021b) to support decision-making in multi-scenario multiobjective optimization problems. This function is constructed in the objective space for analyzing a finite set of Pareto optimal solutions. The value of SB-EAF, at each point of the objective space, is the number (or the percentage) of scenarios that could attain these objective values by at least one solution. Here, by attaining, we mean that each objective function value of the solution under the given scenario is at least as small as the corresponding component of the point. SB-EAF is visualized on a plane for a selected pair of objective functions, limiting the attainability to this pair. Each region of the same attainment function value is filled with a different color.

For each solution, the SB-EAF value is constructed from s objective vectors, each corresponding to a different scenario (see Shavazipour et al. (2021b) for details). SB-EAFs are utilized to visually distinguish different regions of the objective space that may be attained by a given number (percentage) of scenarios (also called attainment surface) for each considered solution. If we compute and visualize the combination of the SB-EAF values of multiple solutions (with corresponding decision vectors) in a single plot, the visualization is called an all-in-one SB-EAF. This visualization gives the DM an opportunity of comparing different attainment surfaces of multiple solutions at a glance. We refer the reader to Shavazipour et al. (2021b) for the details and various illustrative examples. We use the SB-EAF concept and relevant visualizations to analyze the results of our case study in Section 4.

3 Case study

The forest landscape management problem considered here aims at selecting a management regime for each forest stand to optimize predicted long-term outcomes in terms of ecosystem services provided by the landscape. To be more specific, we consider a real four-objective forest management problem from Triviño et al. (2017) and extend it to a multi-scenario multiobjective optimization problem. Next, we briefly describe the problem and real-life data collected in Triviño et al. (2017). Then, we describe our modification and present the mathematical problem formulation.

3.1 Study area and source data

The study area considered in Triviño et al. (2017) is a forest landscape located in Central Finland with 68 700 hectares. The landscape is divided into 29 666 forest stands. Up to 7 possible management regimes can be independently applied to each stand. Each regime defines rules for conducting operations in the forest such as final harvest, thinning, planting or seeding trees, and site preparation. The recommended management regime, referred to as *business as usual (BAU)*, aims at increasing revenue. Most of the other regimes are modifications of this BAU regime and, contradictory, aim to increase the forest's conservation value. The considered regimes are briefly described below (for details, see Mönkkönen et al. (2014); Triviño et al. (2017)).

- *Business as usual (BAU)* – the recommended management regime in Finland aimed at optimizing timber production, with an average rotation length of 80 years.
- *Green tree retention (GTR30)* – BAU with the additional rule that 30 green trees per hectare are retained during final harvest.
- *Extended rotation for 10 years (EXT10)* – BAU with final harvest postponed by ten years.
- *Extended rotation for 30 years (EXT30)* – BAU with final harvest postponed by thirty years.
- *No thinning long rotation (NTLR)* – BAU with no thinning operations (which results in slightly longer rotation length compared to BAU).
- *No thinning short rotation (NTSR)* – a modification of BAU with no thinning, and final harvest criteria adjusted in order to obtain similar rotation length as in BAU.
- *Set aside (SA)* – the conservation strategy where no management activities are carried out during the planning horizon.

Using forest inventory data and forest growth simulator MOTTI (Hynynen et al., 2005), values of essential parameters of forest growth were predicted for each stand under each management regime for a 50-year planning period. For each stand and each regime, these 50-year time series of parameter values were aggregated into four different quantities representing different types of characteristics of good forest management:

1. *timber harvest revenues* as the net present value discounted at 3% interest rate;
2. *carbon storage* in living and dead wood as well as extracted and residual timber;
3. *volume of deadwood*, which is an essential biodiversity indicator;
4. *habitat availability indicator* combination of habitat availability indices for six vertebrate species representing various types of habitat – three-toed woodpecker (Picoides tridactylus), lesser-spotted woodpecker (Dendrocopos minor), flying squirrel (Pteromys Volans), capercaillie (Tetrao urogallus), long-tailed tit (Aegithalos caudatus), and hazel grouse (Bonasia Bonasa).

Given a combination of management regimes selected across stands (one regime for each stand), the values of the above-mentioned characteristics for the whole forest landscape are calculated as sums of corresponding values for each stand. These values constitute four objective functions of our forest landscape management problem, where each objective is to be maximized.

The problem data published in Triviño et al. (2017) includes four matrices playing the role of coefficients of the corresponding objective functions. In each matrix, rows are forest stands, columns are regimes, and each element is the value of the corresponding characteristic for this stand under this regime.

3.2 Scenarios and data generation

We consider three sources of deep uncertainty that are independent of each other: (1) climate change, (2) forest thinning subsidies, and (3) compensation for forest landscape conservation. For each source, we consider so-called “partial scenarios” that represent future possibilities related to this source. Each combination of the partial scenarios forms one scenario in terms of the problem formulation. We consider three, two, and two partial scenarios, respectively, for the above-mentioned uncertainty sources resulting with $3 \times 2 \times 2 = 12$ scenarios in total. The partial scenarios are listed below.

- *Climate change*: in addition to the *stationary climate* scenario (i.e., no climate change), we consider two climate change scenarios established by the Intergovernmental Panel on Climate Change (IPCC) based on the amount of greenhouse gas emissions: B1 (low emissions) and A2 (high emissions) (see, e.g., Nakicenovic et al., 2000).

- *Forest thinning subsidies*: a forest owner in Finland can apply for government subsidies related to young forest management. This results in two partial scenarios (subsidies are granted or not).
- Landscape conservation compensations : a Finnish forest owner can also apply for voluntary agreement programs providing compensation payments for nature conservation. This results in two partial scenarios (the application is accepted or not).

The original problem data corresponds to the scenario composed of stationary climate and the negative decisions on both thinning subsidies and compensation for landscape conservation. Generating the coefficient matrices for the rest of the scenarios was done by modifying the original matrices. First, all four matrices were modified to account for climate change, and then the elements of the timber revenue matrix were increased by adding values corresponding to thinning subsidies and/or compensation for landscape conservation. Thus, the climate change uncertainty influences all the coefficient matrices, while the other two uncertainties influence only the timber revenue matrix.

There is no data concerning the effects of the above scenarios explicitly collected for the considered forest landscape. However, we did not aim at making a decision to be implemented in practice. Rather than that, we tried to create a problem that looks realistic for an expert on forest management planning. Therefore, we did all the modifications using relevant information published in the literature, and filling in information gaps based on realistic assumptions. The process of modifying the coefficient matrices is described in detail in Appendix A.

3.3 Mathematical problem formulation

The forest management problem is formulated as a special case of the multi-scenario multiobjective optimization problem (1), where the objective functions and the set of feasible solutions are defined, respectively, as follows:

$$\begin{aligned}
&\text{minimize} && f_{it}(\mathbf{x}) = -\sum_{h=1}^{p} \sum_{j\in\rho_h} a_{hj}^{it} x_{hj}, && i=1,\dots,k,\ t=1,\dots,s,\\
&\text{subject to} && \sum_{j\in\rho_h} x_{hj} = 1, && h=1,\dots,p,\\
& && x_{hj}\in\{0,1\} && h=1,\dots,p,\ j\in\rho_h,
\end{aligned} \tag{6}$$

where, the number of objectives is $k = 4$, the number of scenarios is $s = 12$, and $p = 29\,666$ is the number of forest stands. For each stand h, $\rho_h \subseteq \{1, \ldots, r\}$ denotes the subset of management regimes that can be applied to this stand, where $r = 7$ denotes the number of management regimes. Each coefficient a_{hj}^{it} represents the outcome of applying regime j to stand h in terms of the i-th objective under the t-th scenario. The components x_{hj} of the feasible solution $\mathbf{x}$ are binary variables defined for all pairs $(h, j),\ h = 1, \ldots, p,\ j \in \rho_h$. Thus, the dimension of the decision space is $n = \sum_{h=1}^{p} |\rho_h|$. This problem can be classified as a mixed-integer linear optimization problem, namely a multiobjective multiple choice knapsack problem.

In terms of the above notation, the problem data is represented by matrices $A^{it},\ i = 1, \ldots, k,\ t = 1, \ldots, s$, with missing elements $A^{it} = \left(a_{hj}^{it}\right)$, where the elements are defined for $h \in \{1, \ldots, p\},\ j \in \rho_h$. Matrices $A^{i1},\ i = 1, \ldots, k$, represent the original problem data and for the rest of scenarios $t = 2, \ldots, s$, the matrices are generated as described in Subsection 3.2.

4 Results

4.1 Interactive decision-making process

We have implemented the decision support environment in a Jupyter Notebook and used a Microsoft Excel worksheet as an interface for exchanging information with the DM. In our experiment, the DM was an expert in forest management. To solve the mixed-integer optimization problem, we utilized Gurobi optimizer. The code and data are freely accessible at `https://github.com/industrial-optimization-group/Interactive-decision-support-and-trade-off-analysis-for-sustainable-forest-landscape-planning-under-`.

Following the proposed Algorithm 1, the solution process was started by calculating the ideal and nadir values for all objectives and scenarios and presenting them to the DM (*step 1 in Algorithm 1*). These values are shown in Table 1. The table also contains numbers assigned to scenarios for quick reference. The scenarios are grouped based on the climate change partial scenarios, since this source of uncertainty is the most influential on the objective function values.

Iteration 1.

First, the DM was asked to choose a few scenarios for which he was willing and able to provide aspiration levels (for all objective functions) and fill in the corresponding cells in the Microsoft Excel table (*step 2a in Algorithm 1*). The DM sought to compare trade-offs between the stationary climate scenario and the high-emission (A2) climate scenario by choosing the *1st* and *4th* scenario from the former group, and *9th* and *11th* scenario from the

Table 1: Ideal and nadir values for each objective in each scenario. M: million, K: thousand.

Scenario			No.	Nadir/Ideal	Revenues	Habitat availability	Carbon storage	Deadwood volume
Stationary climate	No compens.	No Thin. Sub.	1	Nadir	31.77 M	10.81 K	2.83 M	66.93 K
				Ideal	249.97 M	20.23 K	4.45 M	218.15 K
	Compens. gained	No Thin. Sub.	2	Nadir	127.09 M	10.81 K	2.83 M	66.93 K
				Ideal	272.68 M	20.23 K	4.45 M	218.15 K
	No compens.	Thin. Sub. gained	3	Nadir	34.07 M	10.81 K	2.83 M	66.93 K
				Ideal	283.05 M	20.23 K	4.45 M	218.15 K
	Compens. gained	Thin. Sub. gained	4	Nadir	127.74 M	10.81 K	2.83 M	66.93 K
				Ideal	301.46 M	20.23 K	4.45 M	218.15 K
B1 Climate change	No compens.	No Thin. Sub.	5	Nadir	33.87 M	10.69 K	3.01 M	78.03 K
				Ideal	272.69 M	20.24 K	4.89 M	279.94 K
	Compens. gained	No Thin. Sub.	6	Nadir	130.53 M	10.69 K	3.01 M	78.03 K
				Ideal	291.94 M	20.24 K	4.89 M	279.94 K
	No compens.	Thin. Sub. gained	7	Nadir	36.16 M	10.69 K	3.01 M	78.03 K
				Ideal	297.26 M	20.24 K	4.89 M	279.94 K
	Compens. gained	Thin. Sub. gained	8	Nadir	131.18 M	10.69 K	3.01 M	78.03 K
				Ideal	314.58 M	20.24 K	4.89 M	279.94 K
A2 Climate change	No compens.	No Thin. Sub.	9	Nadir	35.96 M	10.59 K	3.17 M	89.19 K
				Ideal	296.54 M	20.29 K	5.34 M	341.39 K
	Compens. gained	No Thin. Sub.	10	Nadir	133.96 M	10.59 K	3.17 M	89.19 K
				Ideal	312.76 M	20.29 K	5.34 M	341.39 K
	No compens.	Thin. Sub. gained	11	Nadir	38.25 M	10.59 K	3.17 M	89.19 K
				Ideal	314.38 M	20.29 K	5.34 M	341.39 K
	Compens. gained	Thin. Sub. gained	12	Nadir	134.60 M	10.59 K	3.17 M	89.19 K
				Ideal	330.40 M	20.29 K	5.34 M	341.39 K

latter group. The DM's reasoning was to keep the timber revenue moderate while seeking more enhanced environmental benefits in the high-emission (A2) climate scenarios compared to the stationary climate scenarios. His preferences are highlighted in blue in the resulting matrix of aspiration levels shown in Table 2.

To get missing preferences, we calculated simulated preferences based on the moderate style (problem (4)) according to the DM's choice (*step 3 in Algorithm 1*). They can be seen in Table 2 in black. The DM wished to skip the step of reviewing the simulated preferences (*step 4 in Algorithm 1*). Therefore, we proceeded to the next step of deriving a Pareto optimal solution to the 48-objective problem (1) by minimizing the achievement scalarizing function (2). Then, the obtained solution (illustrated in a parallel coordinate plot in Figure 3) was presented to the DM (*step 5 in Algorithm 1*).

It turned out that the trade-offs between objectives in various climate change scenarios are more intensive than the DM expected. Comparing the objective function values in various scenarios exposed trade-offs between revenue, habitat availability, and carbon storage in the Stationary climate scenarios and the high-emission (A2) climate scenarios. Furthermore, it seemed that the DM was too optimistic about environmental objectives, in particular, for the deadwood and habitat availability objective functions whose values were significantly lower than what the DM desired. Learning about this fact, the DM decided to lower his expectations related to these two objectives in all scenarios (*step 6 in Algorithm 1*).

Table 2: Aspiration levels in the first iteration. Actual aspiration levels (set by the DM) are highlighted in blue, while the simulated ones are shown in black (M: million, K: thousand).

Scenario	Revenues	Habitat availability	Carbon storage	Deadwood volume
$\mathbf{s_1}$	**170.00 M**	**15.00 K**	**3.70 M**	**140.00 K**
s_2	219.32 M	17.52 K	3.90 M	175.34 K
s_3	191.80 M	17.52 K	3.90 M	175.34 K
$\mathbf{s_4}$	**170.00 M**	**16.00 K**	**3.90 M**	**160.00 K**
s_5	185.16 M	17.50 K	4.25 M	222.79 K
s_6	232.79 M	17.50 K	4.25 M	222.79 K
s_7	201.57 M	17.50 K	4.25 M	222.79 K
s_8	247.36 M	17.50 K	4.25 M	222.79 K
$\mathbf{s_9}$	**180.00 M**	**17.00 K**	**4.20 M**	**250.00 K**
s_{10}	247.23 M	17.50 K	4.60 M	270.00 K
$\mathbf{s_{11}}$	**180.00 M**	**17.50 K**	**4.40 M**	**270.00 K**
s_{12}	258.64 M	17.50 K	4.60 M	270.00 K

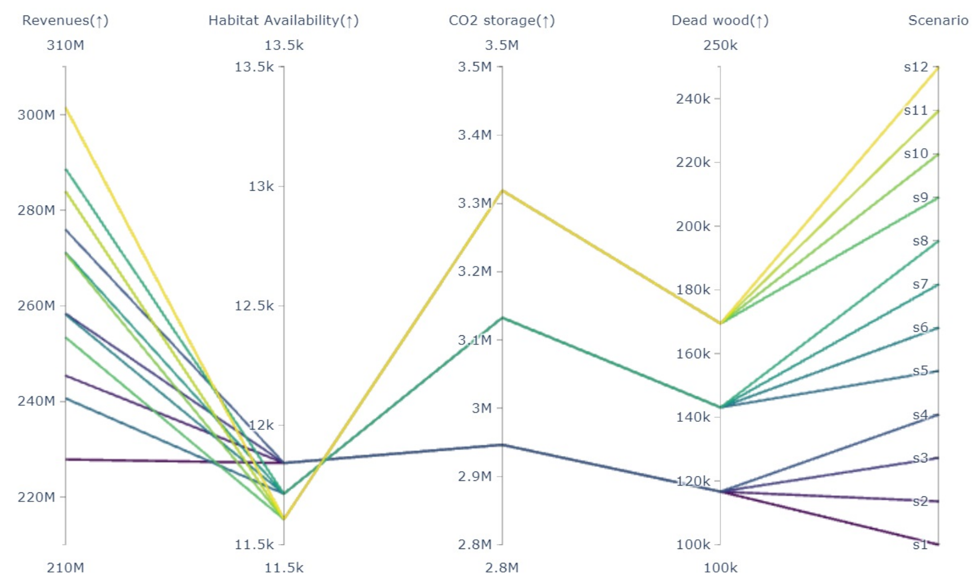

Figure 3: Pareto optimal solution generated by the simulated reference point (moderate style) in the first iteration. Each line represents the objective values in a scenario (s1-s12)—different colors are used to distinguish the achievements in different scenarios. M: million, K: thousand.

Iteration 2. As a result of learning about the problem in the first iteration, the DM set his desired habitat availability values at 10 000 in all the scenarios, reduced the aspiration level for deadwood, and kept the rest of aspiration levels as the previous iteration, which resulted in an updated matrix of aspiration levels shown in Table 3 (*step 2b in Algorithm 1*). We derived the Pareto optimal solution corresponding to the aspiration levels and showed it to the DM (*step 5 in Algorithm 1*). The solution is presented in Figure 4.

This time, the solution had higher environmental values at the expense of a few million EUR lower revenues in various scenarios. For example, in the best-case revenue scenarios (when both compensations and thinning subsidies were included), the revenue decreased by approximately 3–5 million EUR, while in the worst-case revenue scenarios (neither extra compensations nor thinning subsidies were obtained), the decrease was in the range of 14–16 million EUR. However, according to the DM's opinion, the environmental benefits were worth the revenue losses, and he was more satisfied with the obtained solution. Nonetheless, he was curious to check what would happen if he increased the aspiration levels for the third objective (carbon storage) by a few percent, and decided to continue the decision-making process for one more iteration (*step 6 in Algorithm 1*).

Iteration 3. This time, in order to check the potential of increasing the carbon storage objective and analyze the trade-offs between this objective and the other ones in various scenarios, the DM increased the aspiration levels for carbon storage in all scenarios by 5% while keeping the other aspiration levels the same as in the previous iteration, shown n Table 4, (*step 2b in Algorithm 1*). The obtained Pareto optimal solution (*step 6 in Algorithm 1*)

Table 3: Aspiration levels in the second iteration. Actual aspiration levels (set by the DM) are highlighted in blue, while the simulated ones are shown in black (M: million, K: thousand).

Scenario	Revenues	Habitat availability	Carbon storage	Deadwood volume
s_1	**170.00 M**	**10.00 K**	**3.70 M**	**100.00 K**
s_2	219.32 M	**10.00 K**	3.90 M	**100.00 K**
s_3	191.80 M	**10.00 K**	3.90 M	**100.00 K**
s_4	**170.00 M**	**10.00 K**	**3.90 M**	**100.00 K**
s_5	185.16 M	**10.00 K**	4.25 M	**110.00 K**
s_6	232.79 M	**10.00 K**	4.25 M	**110.00 K**
s_7	201.57 M	**10.00 K**	4.25 M	**110.00 K**
s_8	247.36 M	**10.00 K**	4.25 M	**110.00 K**
s_9	**180.00 M**	**10.00 K**	**4.20 M**	**130.00 K**
s_{10}	247.23 M	**10.00 K**	4.60 M	**130.00 K**
s_{11}	**180.00 M**	**10.00 K**	**4.40 M**	**130.00 K**
s_{12}	258.64 M	**10.00 K**	4.60 M	**130.00 K**

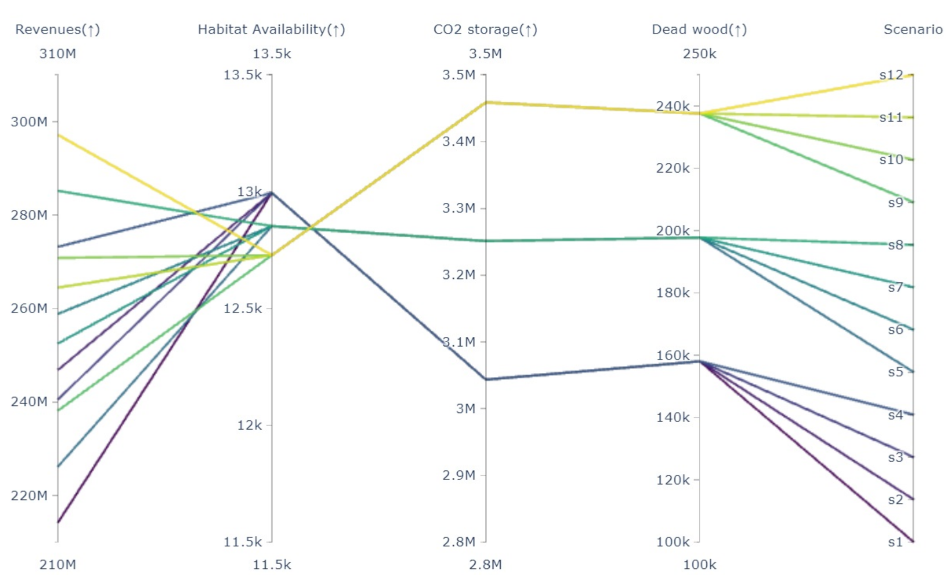

Figure 4: Pareto optimal solution in the second and third (final) iterations. Each line represents the objective values in a scenario (s1-s12)—different colors are used to distinguish the achievements in different scenarios. M: million, K: thousand. M: million, K: thousand.

coincided with the one from the previous iteration, suggesting that the previous solution was stable for such a slight change of preferences. Therefore, the DM concluded that the last Pareto optimal solution can be considered the final one, and the decision-making process was stopped (*step 7 in Algorithm 1*).

Table 4: Aspiration levels in the third iteration

Scenario	Revenues	Habitat availability	Carbon storage	Deadwood volume
s_1	**170.00 M**	**10.00 K**	**3.89 M**	**100.00 K**
s_2	219.32 M	**10.00 K**	**4.10 M**	**100.00 K**
s_3	191.80 M	**10.00 K**	**4.10 M**	**100.00 K**
s_4	**170.00 M**	**10.00 K**	**4.10 M**	**100.00 K**
s_5	185.16 M	**10.00 K**	**4.47 M**	**110.00 K**
s_6	232.79 M	**10.00 K**	**4.47 M**	**110.00 K**
s_7	201.57 M	**10.00 K**	**4.47 M**	**110.00 K**
s_8	247.36 M	**10.00 K**	**4.47 M**	**110.00 K**
s_9	**180.00 M**	**10.00 K**	**4.41 M**	**130.00 K**
s_{10}	247.23 M	**10.00 K**	**4.83 M**	**130.00 K**
s_{11}	**180.00 M**	**10.00 K**	**4.62 M**	**130.00 K**
s_{12}	258.64 M	**10.00 K**	**4.83 M**	**130.00 K**

4.2 Trade-off analysis through visualizations

To get more insight into the problem and provide better support for the DM in our complex problem, we use the visualization methods proposed by Shavazipour et al. (2021b) for decision support in scenario-based multiobjective optimization. Therefore, as proposed by Shavazipour et al. (2021b), we start with the *all-in-one SB-EAF* visualization. We refer to the Pareto optimal solutions obtained in the first and the second iteration as solutions 1 and 2, respectively. We selected the first two objectives (timber revenue and habitat availability) for comparison because their conflict was the most important from the DM's perspective. This visualization is presented in Figure 5. One can clearly see the trade-offs between the two objectives and the performance of the solutions in different scenarios.

The dark purple area (■) represents the worst attainment surface that guarantees the objective values achievable in all scenarios. This worst attainment surface for solution 1 is bounded by 228.118 million EUR revenue and 11.6 thousand habitat availability indicator value. For solution 2, the worst attainment surface shrinks to 214.128 million EUR in revenue but expands to 12.729 thousand in habitat availability, highlighting the trade-offs between these two objectives. This means that solution 2 provides higher environmental values (+1.129 thousand in habitat availability) at the expense of about 14 million EUR lower revenues in the worst-case scenario compared to solution 1. In contrast, the yellow area (■) corresponds to the best possible attainment surface (that only can happen in one scenario—the best-case scenario). Other colors describe the attainment surfaces corresponding to some other ranges of a percentage of scenarios. For example, if the DM sets aspiration levels at 250 million EUR for revenue and 12.5 thousand for habitat availability, he can simply compare how well these two solutions can reach his desired values by taking a glance at Figure 5. Comparing the solutions in this figure shows that the desired revenue can be obtained in at least 75% or 50% of scenarios if the DM chooses solution 1 or 2, respectively. However, it is not possible to reach the 12 thousand value for habitat availability by choosing solution 1, while reaching this value is guaranteed under the conditions of any scenario for solution 2.

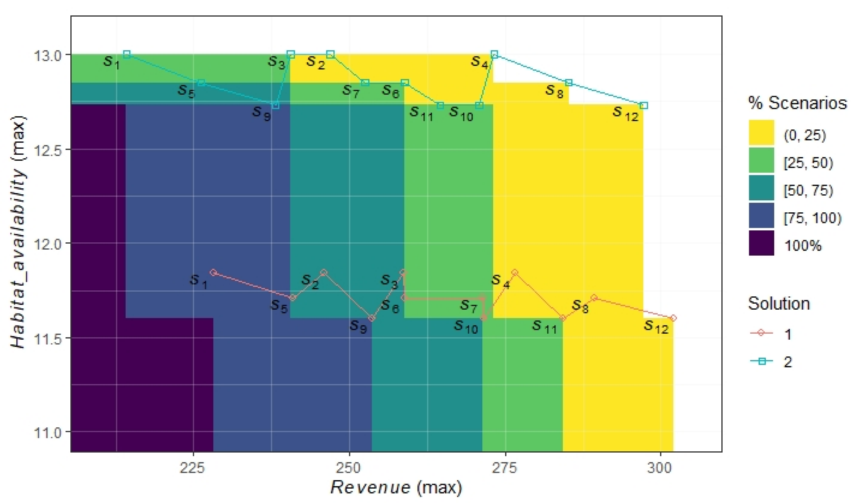

Figure 5: All-in-one SB-EAF visualization of two solutions for timber revenue and habitat availability under 12 scenarios. Points connected by a line denote a solution evaluated on different scenarios. Colored areas show regions of the objective space that can be attained within a particular percentage of scenarios by a solution.

As mentioned in the introduction, the SB-EAF visualization discussed above is only suitable for comparing two objectives at a time. In Figure 6, we utilize the scenario-based heatmaps visualization (Shavazipour et al., 2021b) to compare the two Pareto optimal solutions with regard to all four objectives under all scenarios. Darker colors represent higher objective function values. It can be seen that solution 2 provides higher values for the last three objectives (i.e., carbon storage, deadwood, and habitat availability). Regarding the first objective (timber revenue), solution 1 gives higher values except for the 2nd and 6th scenario.

The visual analysis confirms the result obtained by Triviño et al. (2017), stating the possibility of significant improvements of the multifunctionality of the forest landscape (in terms of the biodiversity objectives) at the expense of a slight revenue reduction. Moreover, in the 2nd and 6th scenarios, solution 2 provides better values for all four objective functions than solution 1. In other words, if one of these two scenarios happens, the improvements of the multifunctionality of the forest landscape (in terms of the biodiversity objectives) can also bring more revenue than the revenue-focused solution (i.e., solution 1) in our problem. This valuable insight could not be gained without separate consideration of scenarios and studying trade-offs between them, as proposed in this study. However, generalizing this fact needs more in-depth investigations in various real cases.

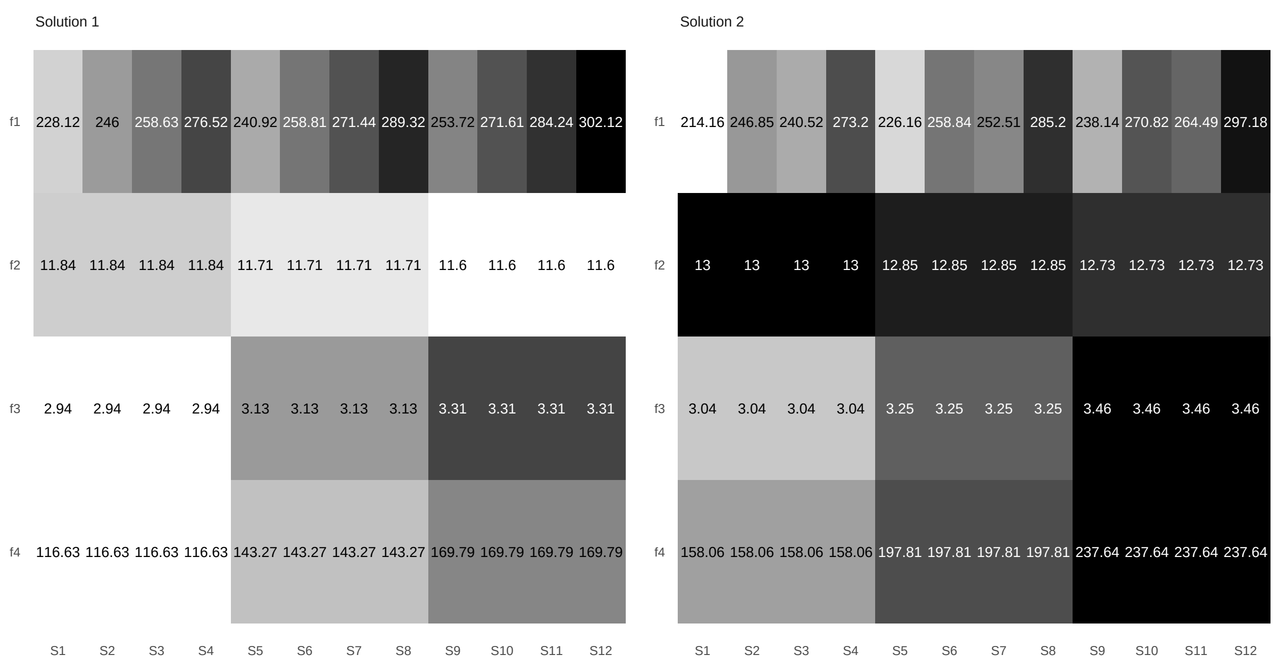

Figure 6: Comparing two Pareto optimal solutions in twelve scenarios via Heatmaps. Darker values are better (all objectives are to be maximized). $f1$: Revenues (million EUR), $f2$: Habitat availability (thousand), $f3$: Carbon storage (million MgC), $f4$: Deadwood volume (thousand m^3).

5 Discussion

In our experiment, the DM found the option of simulating the preferences reasonable and helpful in reducing the cognitive burden of setting preferences in all scenarios. Indeed, although the consideration of all generated scenarios is crucial in finding a robust solution, not all the scenarios may be highly interesting for the DM, or the DM may lack confidence regarding the importance of some scenarios at the beginning of the solution process. Indeed, as a human, the DM may have some expectations and imagination based on their experiences and judgments. For example, the DM might (truly or mistakenly) foresee the likelihood of some scenarios as low (even though one cannot calculate the likelihood of the scenarios in deep uncertainty) or be less concerned about the effect of some sources of uncertainty on planning outcomes (e.g., not expecting significant loss or potential noteworthy gains). On the other hand, interesting scenarios can be interpreted as ones that the DM is expected to be realized more likely or to significantly affect planning outcomes in a good (best-case scenario) or harmful (worst-case scenario) way.

Indeed, it is vital to identify vulnerability/fragility in a system (as critical scenarios) and investigate the consequences of candidate solution(s) on those scenarios. For instance, in our case study, the worst-case financial scenario is when neither compensations for landscape conservation nor thinning forest subsidies could be gained. Therefore, it might be necessary for the DM to track the revenue values in that scenario and ensure it does not lead to a financial crisis. Alternatively, assuring enough environmental benefits (e.g., based on some agreement) in high-emission (A2) climate scenarios might make these scenarios important/interesting for a DM, so that their changes should be tracked more closely. These kinds of scenarios are sometimes called vulnerable scenarios (i.e., scenarios that cause poor performance in some objectives). If so many scenarios are generated for a problem, identifying vulnerable scenarios requires more systematic approaches, such as scenario discovery approaches (see, e.g., Bryant and Lempert (2010); Shavazipour et al. (2021a)). Considering such vulnerable scenarios and the performance of the solutions in terms of various objectives is essential in finding robust solutions. Besides, the DMs may have preferences/feelings on considering some particular scenarios and comparing the objective values and trade-offs with other scenarios (e.g., the current, average, the most probable, or the best-case scenarios).

Furthermore, observing and comparing the ranges of different objective functions across the scenarios and analyzing their interdependencies and trade-offs helped the DM get a deeper insight into the problem and decision-making process. For Our DM, it was more convenient to update the aspiration levels when studying the trade-offs between objectives in various scenarios. Moreover, although the DM was quite satisfied with the solution, he wanted to compare the solutions and trade-offs under different scenarios in more detail. The visualization approaches proposed recently proved to be useful in trade-offs and scenario analysis and find the most preferred robust solution.

We acknowledge the importance of generating the set of scenarios, but it is outside the scope of this paper. Generally, two approaches are most often used in the literature: 1) using experts' judgment, as was done in our case study, and 2) random generation of the scenarios (e.g., when only possible ranges of some uncertain parameters are known). However, in either case, generated scenarios should reflect the significant vulnerabilities of the system/phenomena as well as the DM's preferences (Giudici et al., 2020). Nevertheless, considering too many scenarios is inefficient. On the one hand, the problem may become computationally expensive, and on the other hand, the performances of solutions may be very similar in an ample portion of the scenario space. Utilizing the DM's preferences in reducing the number of scenarios is in line with the philosophy of scenario planning (Ram et al., 2011; Shavazipour et al., 2020).

The calculations were performed on a laptop computer with Intel CORE i7 CPU and 16 GB RAM. All calculation times were short, and the preference simulations took only a few seconds. Solving the resulting mixed-integer problem (2) took $1-2$ minutes each time. This is a surprising result taking into account that the problem has 31 continuous and 152 281 integer variables. The most time-consuming part was creating the multiobjective optimization problem within the Gurobi solver (due to a large amount of data), which took $13-14$ minutes. However, this had to be done only once before the solution process started, and did not cause any waiting time for the DM. Nonetheless, one should be aware of possible longer solution times in case of larger problems (e.g., when more scenarios, objectives, management regimes, and stands are involved).

6 Conclusions

In this study, we proposed a novel interactive approach to handle several important challenges of real decision-making situations in forest management. The challenges are: dealing with multiple sources of deep uncertainty, dealing with incomplete preferences, and treating conflicts between various sustainability objectives such as timber revenue, carbon storage, and biodiversity (including habitat availability and deadwood indicators). In contrast to previous approaches to decision support in forest management, the proposed approach supports the DM in investigating a large variety of characteristics of forest planning and studying conflicts between objectives in various future scenarios. In this way, the DM can get deeper insight through various possibilities reflecting the unknown future and avoid extreme losses. Moreover, the interactive nature of the preference elicitation and solution processes reduces the problem's complexity and the cognitive load of the DM. It provides a more peaceful environment for the DM to learn about the attainability of one's preferences as well as the limitations of the problem in different realization of future scenarios. This helps to find the most preferred solution to such a complex decision problem confidently.

The benefit of investigating possible outcomes in different plausible future scenarios is that the DM can gain more profound and more realistic insights into the problem, the consequences of alternative management strategies in various plausible scenarios, and their overall robustness. It is vital for the DM to analyze the consequences of potential strategies in the various realization of the future and not be fooled by a simple average or a most probable scenario (what is usually done in regular probabilistic methods), which may lead to failures in the case of a different realization of uncertainty. Indeed, the proposed approach helps the DM ensure that the chosen management strategy is robust enough and works relatively well in a wide range of scenarios.

The proposed approach can also be applied in other decision-making problems for different objective functions and sources of uncertainty. For instance, in this study, for simplicity, we only considered three scenarios for climate change. As a future direction of research, it is interesting to consider more climate change scenarios (e.g., among 40 SRES (Special Report on Emissions Scenarios) emissions scenarios developed by IPCC (Nakicenovic et al., 2000)). It would also be beneficial to consider combinations with other sources of uncertainty to analyze how robust the current strategies are. Some work needs to be done for more advanced estimation of the objective function coefficients under different scenarios, for example, augmenting predictions with expert judgments.

As discussed, the current study was the first attempt to address some challenges of extending interactive multiobjective optimization methods for considering multiple sources of deep uncertainty, providing better support for robust decision-making in environmental planning. The next step is extending the proposed approach to dynamic multi-stage decision-making problems, allowing for the consideration of adaptive decisions and contingency plans (Haasnoot et al., 2013) for each scenario. This way, we can better handle deep uncertainty by monitoring and adapting the plan in our continuously changing future, further improving the resistance of forests to climate change and other sources of deep uncertainty.

Software availability

All code used for this research can be found at `https://github.com/industrial-optimization-group/Interactive-decision-support-and-trade-off-analysis-for-sustainable-forest-landscape-planning-under-`.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Models and Multiobjective Optimization (DEMO, jyu.fi/demo) of the University of Jyvaskyla.

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Appendix

A Modification of coefficient matrices for multiple scenarios

As described in subsection 3.2, each scenario is a combination of partial scenarios of three types. The rules of modification are introduced separately for each type of partial scenarios. The climate change scenarios result in multiplying of coefficients by certain ratios, while both types of monetary-related scenarios result in adding subsidy values to the coefficients of the timber revenue objective function. The combined modification is obtained by first applying the climate change modification and then the other two modifications. Below we describe the modification rules for each of these three scenario types.

A.1 Modification for climate change scenarios

Due to the complexity of forest ecosystems, the effects of climate change likely differ for individual forest stands. In the absence of exact models, we simulate this complex nature by introducing randomness in the modification rules. Namely, for each objective function and management regime, we introduce two values: $r^{\min} < r^{\max}$, and multiply each coefficient by the random number generated in the interval $[r^{\min}, r^{\max}]$:

$$r^{\min} + g(r^{\max} - r^{\min}),$$

where g is the geometric mean of two independent, uniformly distributed random numbers between 0 and 1. The shape of the obtained distribution is similar to the normal distribution (Wilson and Martin, 2006). Thus, creating realistic modification rules is reduced to defining values $r^{\min}$ and $r^{\max}$ for all objective functions under the two additional climate change scenarios.

In order to define the realistic values for *the timber revenues and carbon storage objectives*, we use the study of the effects of climate change on timber production and carbon storage published by Garcia-Gonzalo et al. (2017). The paper contains estimations of the two mentioned indicators under the current climate and the climate change scenario HadCM2 for four different management regimes and four types of tree age distributions. We calculated the ratios of change of the indicators caused by climate change. For each selected management regime, we defined $r^{\min}$ and $r^{\max}$ as the minimum and maximum ratios obtained, respectively, across the four distributions of tree age.

For management regimes without thinning (SA, NTLR and NTSR), we used ratios corresponding to the regime without thinning studied in the paper, which results in the values $r^{\min} = 1.0699$, $r^{\max} = 1.1350$ for the timber revenues objective and $r^{\min} = 1.1304$,

$r^{\max} = 1.1408$ for the carbon storage objective. For the rest of our management regimes, we used the ratios calculated from the paper for the BAU management regime: $r^{\min} = 1.0851$, $r^{\max} = 1.1701$ for the timber revenues objective and $r^{\min} = 1.0500$, $r^{\max} = 1.1053$ for the carbon storage objective.

Note that the above values are defined based on data for the climate change scenario HadCM2. As follows from the description of the scenarios, HadCM2 can be considered as an intermediate between B1 and A2. As a rule of thumb, we defined the values of $r^{\min}$ and $r^{\max}$ for scenarios B1 and A2 by multiplying the corresponding values obtained based on scenario HadCM2 by 0.75 and 1.5, respectively.

In order to define ratios for the *deadwood objective*, we used results published in Mazziotta et al. (2014). The deadwood volume in boreal forests was estimated separately for three wood species under two climate scenarios (current climate and A2) for BAU and SA management regimes. Same as above, for both management regimes, we calculated ratios of change of deadwood volume caused by the climate change, and defined $r^{\min}$ and $r^{\max}$ values as the minimum and maximum ratios, respectively, across tree species. As a result, we obtained $r^{\min} = 1.19$, $r^{\max} = 1.51$ for the BAU management regime and $r^{\min} = 1.33$, $r^{\max} = 1.74$ for the SA management regime. For the rest of the regimes, we used the same values as for BAU since they represent modifications of the latter. In order to obtain $r^{\min}$ and $r^{\max}$ values for B1 climate change scenarios, we divided the corresponding values for A2 scenarios by two as a rule of thumb.

Unlike the other three objectives considered above, in the case of the *habitat availability objective*, we did not find any published data that could be directly used for defining values of $r^{\min}$ and $r^{\max}$. There are papers that can provide some general hints about the effects of climate change on species habitat. For example, in the paper Mazziotta et al. (2016), the effects of three climate change scenarios (B1, A1B and A2) were studied for habitat suitability of species of beetles and fungi associated with boreal forests. The results are in a way contradictory: in terms of the habitat quality aggregated across species, more forest stands are predicted to improve than deteriorate. However, for individual species, more species would have deteriorated habitat suitability than improved. Another paper (Cadieux et al., 2020) describes the effects of two climate change scenarios (RCP 4.5 and RCP 8.5) on 72 bird species in Canadian boreal forests. The authors predict the average growth of habitat quality by 13% under RCP 8.5; however, the changes across species range from -47% to +262%. Finally, it is worth mentioning the report by the Finnish Ministry of the Environment and Statistics (Niinistö et al., 2017) that states: "Climate change is expected to increase the total number of species in the Finnish flora and fauna and will cause a turnover of species. Furthermore, considerable changes are likely to occur in the distribution patterns of species and habitats." Without a clear indication of the direction of change in habitat quality, we assume the possibility of changes in both directions and set $r^{\min} = 0.9$, $r^{\max} = 1.1$ in the case of B1 and $r^{\min} = 0.8$, $r^{\max} = 1.2$ in the case of A2 climate change scenarios independently on the management regime.

A.2 Modification for monetary scenarios

The amounts of subsidies for thinning as well as compensation for landscape conservation are calculated proportionally to the areas of individual forest stands. The publication Triviño et al. (2017) does not contain this information (only the total area of the landscape). Keeping in mind that our purpose is merely generating a problem that looks realistic to a forestry expert, we used estimations of forest stand areas based on the coefficient matrices. For each objective function and each management regime (represented by a column of a coefficient matrix), we calculated the shares of coefficients for all stands in the sum of coefficients, ignoring missing and negative coefficient values. Then for each stand, we calculated the average of shares across all objective functions and regimes. This average share multiplied by the total landscape area serves as the estimation of the stand area.

According to the Finnish Forest Center[1], forest owners can apply for *subsidies covering forest thinning activities*, up to 430 EUR/ha. In the scenario of obtaining the subsidies, we increase the coefficients of the timber revenue objective by 430 multiplied by stand area for all management regimes involving thinning (BAU, EXT10, EXT30, GTR30).

Moreover, in Finland, there are programs providing compensation to forest owners for excluding forest areas from timber production or delaying the cutting process (Mäntymaa et al., 2018). As an example, we assume that there is 30 EUR compensation for delaying harvest per one year, per one ha of forest. Then in the scenario where the forest owner gets compensation, the coefficients of the timber revenues objective are increased as follows: 300 EUR/ha for management regime EXT10 (delaying harvest by 10 years), 900 EUR/ha for EXT30 (delaying harvest by 30 years), and 1500 EUR/ha for SA (setting aside forest, taking into account 50 years planning horizon).

B Proof of model's feasibility

Theorem B.1. *Optimization problem* (4) *is always feasible and bounded.*

Clearly, $\tilde{z}_{it} = \max_{1 \le u \le q} g_{it}^{u}$ *(for all* i*) would be a feasible solution for model* (4)*. Moreover, all the preferences might not be worse than the nadir point (*z_{it}^{nadir}*) nor be infinitely better than the ideal point (*z_{it}^{ideal}*) (which none of them has any infinite component); then, the maximum value for the objective functions is bounded below by* $\sum_{i=1}^{k} |z_{it}^{nadir} - (z_{it}^{ideal} \pm \epsilon)|$

[1] `https://www.metsakeskus.fi/tuki-nuoren-metsan-hoitoon`

which is a finite number and ϵ *(*$0 \leq \epsilon << \infty$*) is a difference between the DM preferences and the ideal point).* ■