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Multi-Objective Sequential Forest Management Under Risk Using a Markov Decision Process-Pareto Frontier Approach

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Abstract

Forests play an important role in many different cycles (carbon sink, biodiversity, timber) and, consequently, in regulating the global climate system. Moreover, forests are the source of a wide range of goods and services to human societies and, as a result, the decisions made by forest owners affect forest ecosystems. Since forests are currently threatened by climate change, there is a need to provide support to forest owners for managing forests under risk, taking conflicting objectives into account. This study focuses on developing an explicit multiple-objective and sequential forest management model under risk. The multi-objective sequential optimization approach used here is based on the concept of Pareto optimality, and the computation of the Pareto frontier (the set of non-dominated solutions), instead of a single solution. We consider a Markov Decision Process (MDP) model to evaluate forest management policies under different criteria, and to generate the Pareto frontier. The framework is applied to the management of a private forest located in southwestern France. We identify optimal forest management practices for each objective separately and trade-off policies considering all objectives jointly. We analyze the forest management policies located on the Pareto frontier, yielding different trade-offs among the conflicting objectives. Our framework makes it possible to envision all possible trade-offs, and to understand how a trade-off policy takes each objective into account. It is hoped that this information will help in analyzing potential policy implications for forest management, taking the provision of multiple forest ecosystem services into consideration.

Keywords Forest management · Risk · MDP · Pareto front

1 Introduction

Ecosystem services (ES) provided by forests such as timber production, global climate regulation through carbon sequestration, recreational uses, and conservation of biodiversity (MEA [3]), are increasingly considered and recognized as fundamental to forest management strategies.

Although forests have traditionally been used for timber harvesting, additional management objectives such as maintenance of biodiversity and carbon sequestration also clearly determine forest management decisions (Stenger et al. [55]; Pukkala [45]). It has been observed that the societal demand for ES has strongly increased over the years, leading to increased pressure on Non-Industrial Private Forest (NIPF) owners to protect such ES. In such a context, timber production, considered as the main economic service, may often be in conflict with other ES because the provision of timber and non-timber ES takes place in the same forest stand (Peura et al. [42]; Pohjanmies et al. [43]; Vauhkonen et al. [58]). However, because many ES are not traded in markets, markets fail to reflect the benefits they provide to society and to regulate their uses, that contribute to the efficient allocation and sustainable benefits of such services (MEA [3]). In this context, forest management recommendations such as postponing timber harvest and preserving biodiversity habitat, while benefiting society, induce financial losses for forest owners (Matta et al. [35]).

Moreover, forests are increasingly threatened by natural events, and the frequency and intensity of extreme events are expected to increase due to climate change (Haarsma et al. [26]), requiring modifications in forest management plans and practices (FAO [20]). The effects of climate change on forest ecosystems vary according to forest ecosystems, are ambiguous, and are not completely understood. Indeed,

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extreme events have multiple effects and major financial consequences, as well as causing strong ecological and environmental damage. Forests are important repositories of ES, which will be directly and indirectly affected by changing climatic conditions. Adapting forest management to these changing and uncertain future conditions can be considered one of the most important challenges for forest owners (Keenan [30]).

With a growing societal demand for a larger set of goods and services from forest ecosystems, and with forests being threatened by climate change, support must be provided to NIPF owners if they are to manage forests under risk, while taking conflicting objectives into account. Moreover, from the forest owner's individual point of view, it has been widely observed that NIPF owners retain timber production as the main forest management objective but also consider non-timber objectives: timber production, recreational aspects, including biodiversity conservation. Many previous empirical studies have analyzed the main objectives of NIPF owners (for some illustrations, see Dominguez and Shannon [17], with forest owners in Spain; Hendee and Flint [28], with forest owners in the state of Illinois; Poje et al. [44], with forest owners in Slovenia; Haugen et al. [27], with Swedish forest owners; Põllumäe and Sepp [46], with forest owners in Estonia). Conway et al. [13] performed an empirical analysis of several NIPF owners' objectives, using a US database. They found that several forest management objectives are taken into account, depending on the characteristics of the environment, the forest, and the forest owner. In the same way, Tian et al. [56] determined the main factors explaining the main selected objectives of the NIPF owners located in Tennessee in managing their forests. They confirmed that NIPF owners manage their forests for ES depending on the forest and the owners' characteristics, as well as the existence of financial incentives. Petucco et al. [41] empirically analyzed the harvesting decision in order to highlight the main forest management objectives of a sample of selected French forest owners, assessing the risk preferences of the forest owners. Khanal et al. [32] focused on the forest carbon sequestration objective for managing private forests using US data. They showed that both recreation and timber benefits are important objectives for the selected forest owners. More recently, Côté et al. [14] precisely studied and explained the difference in several important objectives using a database on NIPF owners located in Canada. They focused on the impact of being a new or an older forest owner on the main forest management objectives.

On the basis of this abundant literature, we concluded that NIPF owners consistently include timber and non-timber objectives to define forest management. Such objectives may be conflicting and difficult to evaluate and compare because of their different units of measurement and the existence or not of a market. It is then necessary to provide support for forest management for NIPF owners in such a context. Incorporating multi-objective optimization in sequential decision-making under uncertainty can help provide efficient plans for the management of different ES, and can be an interesting instrument for guiding choices in the perspective of ecological and economic objectives (Mazziotta et al. [36]; Mönkkönen et al. [38]).

There is a growing literature dealing with the problem of optimal forest management that takes different objectives into account (Borges et al. [5]; Borges et al. [6]; Álvarez-Miranda et al. [1]): in the case of timber production, biodiversity conservation, and carbon sequestration, see Schwenk et al. [51], Nguyen and Nghiem [40]; as for carbon and timber objective, see Johnston and Withey [29]. Nevertheless, the determination of optimal forest age cut for the provision of multiple ES under risk is still a significant challenge to forest management. Common forest economic optimization methods aggregate multiple weighted objectives into a single value (Schwenk et al. [51]; Eggers et al. [18]; Johnston and Withey [29]). These weighted sum approaches involve a high degree of subjectivity. Indeed, weights are often subjective and static, unable to correctly describe the dynamics in ecological and economic systems (Kennedy et al. [31]; Mazziotta et al. [36]). For biodiversity conservation, species presence and richness can be dynamic across time. Biodiversity service weight should also vary accordingly. In the same way, since economic values may change over time, the economic weight may also vary. The corresponding optimal management policies are then very sensitive to the weighting values of the different objectives. Parallel to this classical weight-based approach, an alternative procedure based on the simultaneous maximization of different objectives has been developed. Multi-objective optimization methods are generally based on the concept of Pareto optimality. Such a method has been applied to study optimal forest management plans in a multifunctional forestry context, considering different objectives of timber and non-timber ecosystem service productions, and to analyze trade-offs between economic and ecological objectives (Borges et al. [5]; Mönkkönen et al. [38]; Peura et al. [42]; Bughalo et al. [9]; Pohjanmies et al. [43]; Mazziotta et al. [36]; Triviño et al. [57]; Álvarez-Miranda et al. [1], [2]). These studies that use the Pareto frontier for multi-objective forest management impose restrictions concerning the space alloted to forest management plans (Mönkkönen et al. [38]; Peura et al. [42]; Pohjanmies et al. [43]; Mazziotta et al. [36]). Most studies generally do not consider natural disturbances (Triviño et al. [57]; Borges et al. [5]), with the exception of the studies of Álvarez-Miranda et al. [1, 2]. In the same way, Eyvindson et al. [19] use an interactive multi-objective optimization method combined with a Pareto concept, for forest planning, considering the value-at-risk as the risk measure, but with undiscounted criteria. Under risk, the Markov Decision Process (MDP) models are a frequently used approach for dealing with forest management that takes multiple criteria to be optimized into account. Different types of criteria, discounted or undiscounted, depending on the objectives considered, and that may conflict, can be considered with MDP models. Buongiorno et al. [11] use undiscounted economic and ecological criteria in a MDP model with NIPF owners' risk preferences to obtain optimal forest harvesting policies in a context of multicriteria forest management. They do not consider the time preferences of the forest owner, which are essential for the economic criterion. Zhou and Buongiorno [62] propose a MDP model for optimal forest management that includes NIPF owners' preferences with a discounted criterion. They study the trade-off between their economic criterion and selected ecological criteria, without explicitly considering the problem of multicriteria forest management. Buongiorno and Zhou [10] consider goal programming in a MDP model with discounted and undiscounted criteria to deal with the problem of multicriteria forest management under risk. The principle of this methodology is to fix goals for each criterion, and to find a solution to minimize the sum of weighted deviations from the fixed goals, and to satisfy all the constraints of the problem. The weights reflect the preferences of the forest owner for each objective, and pose the problems mentioned above. This approach can lead to satisfactory but not necessarily optimal solutions.

We define a maximization approach to obtain optimal forest management policies considering different objectives in the same forest stand. In this case, the forest stand is not dedicated to satisfying either an economic or an ecological objective, like in the classical optimization approach, but instead contributes to achieving trade-offs between the different objectives.

The main contribution of this work is to design a MDP model to evaluate forest management policies in a risky context under different criteria, and to generate the Pareto frontier of forest management policies evaluated under several conflicting objectives. This enables the forest owners to develop insights into the economic and ES of forest management.

The paper is structured as follows. Section 2 describes the multi-objective optimization problem under risk and the fundamental principles for solving it. Section 3 presents and discusses the results of an application to a maritime pine stand facing fire risk in southwestern France. The conclusions are summarized in Section 4.

2 Materials and Methods

Similarly to Johnston and Withey [29], the fundamental principle of this study is to use the Markov Decision Process (MDP) framework (Puterman [47]; Sigaud and Buffet [53]) in order to represent the dynamics of the forest ecosystem affected by random disturbances, and to find optimal policies. There are several different objectives corresponding to the different ES to be optimized. Each ecosystem service can be modeled by a different reward function, leading to a specific MDP, for which an optimal policy can be computed (see Section 2.1). However, this approach is not satisfactory. We instead evaluate every single policy along the different ES/MDP and identify the policies that form a Pareto frontier with respect to the objectives (see Section 2.2). At first glance, this task may be overwhelming, due to the number of potential policies. However, we will show in this section it is not the case and further we only need to consider *threshold policies*, defined by a threshold age class after which stands are systematically harvested.

2.1 The Multi-Objective Optimization Problem Under Risk

2.1.1 Definition of Ecosystem Services

In this paper, the overall goal is to manage forests in a context of multiple ES, as represented here by three management objectives: providing timber harvest revenues, storing carbon, and preserving biodiversity.

Timber Harvest Revenue Timber harvest revenue depends on the age of the stand, the price of timber, and the different costs of forest activities. The main goal is to maximize the expected net present (discounted) value of timber harvest revenue over an infinite horizon (Johnston and Withey [29]).

Carbon Storage Carbon storage is calculated based on aboveground biomass estimated using timber volume. The amount of carbon sequestered in a standing forest is directly calculated by the forest's biomass. We use a conversion factor to convert a wood volume into metric tons. According to Stainback and Alavalapati [54], the conversion coefficient is 0.3 metric tons of carbon per cubic meter. The goal for this service is to maximize the average stock of carbon stored over time in standing trees.

Biodiversity Indicators Biodiversity is a complex and controversial concept subject to many studies and its valuation should include many aspects (Saraev et al. [48]). Its assessment involves different concepts and notions: species richness, species diversity, abundance, evenness, whose quantification requires a lot of ecological data. In such context, it is common to use an indicator of biodiversity like species richness or species diversity indices (Bartkowski et al. [4]; Fedor and Zvaríková [21]). In our study area, we rely on simple single species richness as an indicator for biodiversity conservation. It is often acceptable, easily calculable, and frequently used by economists (Bartkowski et al. [4]). More complex indicators such as Shannon-Wiener index or Simpson index (Fedor and Zvaríková, [21]) were not conceivable because of lack of data.

As in Nghiem [39], we use a representative bird population abundance as an indicator for global biodiversity. We choose this species as bird species are frequently considered surrogates for biodiversity (Bughalo et al. [9]). We assume that the abundance of birds only depends on the age of the forest stand. The objective of this service is to maximize the average bird population.

2.1.2 The Optimization Model Structure

We considered a NIPF owner facing a problem of dynamic forest management under fire risk over an infinity of harvesting periods.[1] A harvesting period is denoted d and includes several years.

Throughout the paper, we assume that the private forest owner manages a single plot with one unique tree species. Our approach can be extended to several plots using, for instance, the framework proposed by Couture et al. [15] to handle multiple plots with a single criterion. However, a multiple plots forest management problem involves a larger number of policies to compare. This difficulty will be discussed in the "Conclusion" Section, as well as possible solutions to overcome it.

The MDP framework allows us to efficiently model a sequential decision-making problem under uncertainty and solve the problem of maximizing the expected sum of discounted rewards (Puterman [47]; Sigaud and Buffet [53]). In its classical formulation, an infinite-horizon stationary MDP is described by a four-tuple, $< S, A, p, r >$, where S represents the finite set of states that can be reached by the system, A represents the finite set of decisions that can be applied at each period, p is a probabilistic state transition function, and r is a reward function.

State and Action Variables As shown in Fig. 1, the state of the stand plot is represented by the variable s where $s \in S = \{1, ..., m\}$ is the age class of the stand plot. Let us assume that $s \in \{1, ..., m\}$ with 1 denoting the youngest age class and m denoting the oldest one. m is the age after which trees no longer improve their value. Trees in age class s are characterized by their timber volume v_s, which increases with the age class, i.e., $v_s > v_{s-1} \quad , \forall\ 2 \leq s \leq m$. In each period, the forest manager has to decide whether to harvest the plot or not. The decision for each stand is either to do nothing or to cut down the stand and reforest immediately. Therefore, an action is represented by a decision variable $a \in A = \{1, 2\}$ where $a = 1$ if the stand plot is harvested and $a = 2$ if the stand plot is not harvested.

Risk and Markov Chain Models of Forest Growth The stochastic environment of the forest owner is described by a risk of stand plot destruction due to fire. We assume that fires occur after harvests (see Fig. 1). Let p_a denote the annual probability of a fire. Assuming independent fire risks, the probability of fire within a period of d years is $p_f = 1-(1-p_a)^d$. We assume that if a fire occurs, a given proportion of the timber volume is salvaged.

In the MDP framework, forest growth is described by the transition probabilities between forest states. The application of an action may change the state of the forest. Furthermore, the state of the forest at the next period depends stochastically only on the state of the forest at the current period and on the decision applied. The transition probability between forest states $p(s' \mid s, a)$ is defined as the probability that the system will change from state s in the current time period to state s' in the following one, given that action a has been applied. For the different values of (s, a, s'), these transition probabilities are:

- No harvesting, no fire:
  $p(s' = min(m, s+1) \mid s, a = 2) = 1 - p_f$
- No harvesting, fire:
  $p(s' = 1 \mid s, a = 2) = p_f$
- Harvesting, no fire:
  $p(s' = 1 \mid s, a = 1) = 1 \ \text{ or } \ p(s' \neq 1 \mid s, a = 1) = 0$
- Harvesting, fire:
  $p(s' = 1 \mid s, a = 1) = 1 \ \text{ or } \ p(s' \neq 1 \mid s, a = 1) = 0$

(1)

The transition probabilities (1) depend on the probability of fire within the decision period, and therefore on the annual probability of fire. If the annual probability is changed, then the transition probabilities will also be changed.

Reward Functions Rewards of a plot can be of different nature. In the following, we will consider *timber harvest revenues*, *carbon storage*, and *biodiversity conservation*, modelled respectively by three functions, r_h, r_c, and r_b. Generic rewards are noted r_X for $X \in \{h, c, b\}$.

Timber Harvest Revenues The net revenue of the plot, $r_h(s, a, s')$, depends on the age of the plot, the decision to

[1] When the horizon is infinite, it can be shown that the value function of a stationary policy does not depend on time. For that reason, the time index does not appear in mathematical equations.

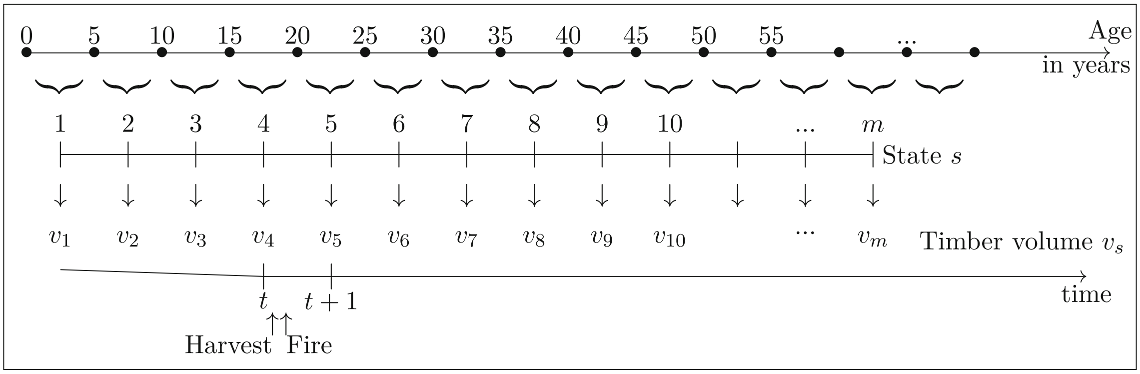

Fig. 1 Definition of states, state variables, and sequence of events for a 5-year period

harvest, and the occurrence of fire. In case of no fire, the timber harvest revenue is defined as:

$$r_h(s, a = 1, s' = 1) = area[v_s(T_s - C_h) - C_p] \quad (2)$$

where $area$ is the area of the plot (in ha), T_s represents the timber price (in €$/m^3$) for age class s, C_h is the harvesting cost (in €$/m^3$), and C_p is the planting cost (in €/ha).

Empirical evidence (Schelhaas et al., [49]) suggests that in the case of fire, the entire production is not lost. Hence, we assume that in the event of an age class destruction, a proportion $\alpha \in [0, 1]$ of the timber volume can be recovered and sold by the forest owner. This proportion corresponds to the percentage of salvaged timber. α equal to 1 means that fire does not result in any timber loss and the only impact of the stochastic event is to impose harvesting at a time that may not be optimal. On the contrary, α equal to 0 means that a destroyed stand yields no revenue. In this context, the net revenue of the plot if not harvested and impacted by a fire is:

$$r_h(s, a = 2, s' = 1) = area[\alpha \cdot v_s(T_s - C_r) - C_p] \quad (3)$$

where C_r is the recovery cost (in €$/m^3$) in the case that the stochastic event occurs. The planting cost depends on the planted area and the harvesting and the recovery costs depend on the timber volume. The net revenue is null for the other cases.

Carbon Storage In forests, carbon is stored in standing trees, until timber is harvested or destroyed by fire. Therefore, carbon storage $r_c(s, a, s')$ depends on the timber volume, the decision to harvest, and the occurrence of fire. We only consider carbon storage in standing timber.

If the plot is not harvested, then the carbon stored is defined by:

$$r_c(s, a = 2, s' = min(m, s + 1)) = area[\lambda v_{s'}] \quad (4)$$

λ denotes the conversion factor to convert a wood volume into metric tons of carbon. If the plot is harvested,[2] then the carbon stored is:

$$r_c(s, a = 1, s' = 1) = area[\lambda v_1] \quad (5)$$

If a fire occurs, then all the carbon storage is lost, and is:

$$r_c(s, a = 2, s' = 1) = area[\lambda v_1] \quad (6)$$

In other words, in both cases, we give some value to the carbon stored in a stand that has just been replanted during the current time period.

Biodiversity Conservation We choose a biodiversity conservation indicator built on the number of bird pairs of a particular species, $D(s)$. The value of this indicator, $r_b(s, a, s') = D(s')$, depends on the age of the stand plot at the end of the period. For a harvested plot or if a fire occurs, biodiversity is highly impacted and the biodiversity conservation indicator is therefore only:

$$r_b(s, a, s' = 1) = D(1) \quad (7)$$

If the plot is not harvested, then the value of the indicator is:

$$r_b(s, a = 2, s') = D(s') \quad (8)$$

Our definition of the reward functions relies on an assumption that a fire event occurs immediately after forest harvest and at the beginning of 5-year periods. Of course, this is a simplified assumption. Harvesting may be more or less continuous along the 5-year period (or occur in several successive steps) and fire events may occur at any time. Modifying our simple model to consider these more realistic situations poses no particular difficulty. However,

[2]As seen in Table 1, we assume that harvesting or fire occurs at the beginning of a period, and that the volume of timber is evaluated at the end of the period. In the case of harvesting, the carbon stored in harvested timber is considered as definitively lost.

it is unlikely that this would make huge differences in our results. Indeed, if we use a linear interpolation for the timber volume increase and linear modifications of carbon storage and biodiversity criterion, the three criterion values will be roughly linearly modified (except for the criterion of discounted timber revenue). Therefore, for the sake of simplicity, we stick to our event timing assumption.

Rewriting of the Reward Functions The three reward functions considered are of the form $r_X(s, a, s')$, i.e., assigned to state transitions. However, it is usual, in the Markov Decision Process framework, to consider state-action rewards, instead of transition-based rewards, when defining the problem. These are defined from the state-transition–based rewards and the transition probabilities, as:

$$\bar{r}_X(s, a) = \sum_{s' \in S} p(s'|s, a) r_X(s, a, s'). \tag{9}$$

Indeed, it is well-known that solving a MDP with state-action rewards computed from the transition-based rewards leads to the same solutions (policy values, optimal policies, etc.) as in the original problem. Rewards are expressed as state-action rewards (which may have been either given in the problem definition or computed from transition-based rewards).

MDP Policy In a MDP, a *deterministic stationary policy* is defined as a function $\pi : S \to A$, which prescribes an action for every possible state of the system. Once fixed, a policy π, together with a transition model p, defines a Markov chain with a transition matrix $P_\pi(s'|s) = p(s'|s, \pi(s))$. Note that the set of available stationary policies is the set of functions from S to A and there are 2^m such policies. Dynamic programming approaches do exist to compute optimal policies, in the case of single-criterion MDP. In general multi-criteria MDP, the problem is more difficult; however, there are several methods relying on dynamic programming approaches to construct the Pareto front (White [60]; Krishnendu et al. [34]; Wiering and de Jong [61]). Nevertheless, as we will see later, it is still possible to propose efficient approaches to compute good compromise policies for multi-objective forest management problems in the single stand case. We will start by defining the different management criteria.

Definition of Criteria and the Corresponding Value Functions As previously indicated, the criteria are of different natures, and are defined according to the services considered. We denote $f_X(\pi)$ the criterion for each service, $X \in \{h, c, b\}$.

Like Zhou and Buongiorno [63], we use the expected discounted rewards over an infinite horizon for evaluating policies with respect to the timber revenue criterion $f_h(.)$, for given initial conditions related to state probabilities $p_0(\cdot)$. Such a criterion strongly depends on the initial distribution of the system, and is defined as :

$$f_h(\pi) = \sum_{s \in S} V_h^\pi(s) p_0(s) \tag{10}$$

$V_h^\pi(s)$ is the value of policy π defined as the expected sum of discounted rewards obtained along the Markov chain P_π for an infinite horizon:

$$V_h^\pi(s) = E\left[\sum_{t=0}^{\infty} \gamma^t \bar{r}_h(s_t, \pi(s_t)) | s_0 = s, \pi\right]$$

with γ the discount factor, and $\bar{r}_h(s_t, \pi(s_t))$ the state-action timber harvest reward.

The criterion for carbon storage $f_c(\pi)$ is the expected value of averaged rewards over an infinite horizon, for given initial conditions, and is defined as:

$$f_c(\pi) = \lim_{T \to \infty} E\left[\frac{1}{T} \sum_{t=1}^{T} \bar{r}_c(s_t, \pi(s_t)) | s_0, \pi\right] \tag{11}$$

with $\bar{r}_c(s_t, \pi(s_t))$ the state-action carbon sequestration reward. As the Markov chain obtained when π is applied has a single recurrent class, the initial state s_0 can be chosen arbitrarily and this criterion is equivalent to:

$$f_c(\pi) = \sum_{s \in S} \mu^\pi(s) \bar{r}_c(s, \pi(s)),$$

where $\mu^\pi(\cdot)$ is the stationary distribution of the Markov chain defined by π (i.e., the proportion of time spent by the stand in each state s).

The criterion for biodiversity conservation, $f_b(\pi)$, is defined in a similar way as the criterion for carbon storage:

$$f_b(\pi) = \sum_{s \in S} \mu^\pi(s) \bar{r}_b(s, \pi(s)),$$

where $\bar{r}_b(s, \pi(s))$ is the state-action biodiversity reward.

Optimal Policies for the Different Criteria Let us define one MDP $MDP_X = (S, A, p, \bar{r}_X)$ for each of the three criteria. MDP_h is a *discounted* MDP, with discount factor γ, while the other two MDPs are *average* MDPs. All these can be efficiently solved to optimality using *dynamic programming* or *linear programming* algorithms (Puterman [47]). Policy values can also be efficiently computed. Available tools can be used to perform numerical policy evaluation and optimization, e.g., the Matlab MDPtoolbox of Chades et al. [12] (see Section 3).

However, the MDP_X problems have a particular property that makes it possible to simplify their solution. Indeed, with our problem, only the $m + 1$ *threshold policies*

$\pi_k, k = 0...m$, where $\pi_k(s) = 1$ if and only if $s > k$, i.e., cut trees aged strictly more than k, are realistic and need to be considered for finding an optimal policy. The general idea is that, when a policy requires to cut a state s, actions required to cut for states $s' > s$ will never be applied, except at the initial state. Indeed, any MDP_X and arbitrary π define a stationary Markov chain of the transition matrix P_π. The *threshold policies* π_k require keeping only trees of age less than the age of the first prescribed cut in π : $k \leftarrow min\{s, \pi(s) = 1\} - 1$. Remark that:

1. P_π has a single recurrent class and has the same stationary distribution as P_{π_k} ($\mu^\pi = \mu^{\pi_k}$).
2. If the support of the distribution of p_0 is $\{1, \ldots, k\}$, P_π and P_{π_k} result in the same state distributions at every time step, when p_0 is the initial distribution. Indeed, the transition probabilities $P_\pi(s'|s)$ and $P_{\pi_k}(s'|s)$ are equal, for $s \in \{1, \ldots, k\}$ and any $s' \in S$. Furthermore, $P_\pi(s'|s) = P_{\pi_k}(s'|s) = 0$ for $s' > k$.

Point 1 implies that for any non-threshold MDP policy, a threshold policy exists with an average criterion value at least as good. Point 2 implies that the same property holds for discounted MDP (i.e., MDP_h), provided that $p_0(s) = 0, \forall s > k$. This assumption for p_0 is limiting. However, it can be observed that, due to fire risk, any Markov chain P_π has the same recurrent class as P_{π_k} and that $s = 1$ belongs to this recurrent class. It can then be noted that under policy π, state 1 will be reached with probability 1 at some time, as of which the state will follow the same Markov chain under both policies. Thus, the optimal threshold policy, even if not optimal for the discounted criterion for initial states above the threshold, can be seen as optimal "in the long run." Consequently, even if threshold policies only approximate optimal policies in the discounted case, we will limit our study to them.

The advantage of considering threshold policies is that only such policies need to be evaluated with respect to the three criteria, using dynamic programming (or linear programming or other efficient approaches). The multi-criteria comparison of policies is then decoupled from the (easier) problem of evaluating policies according to the different criteria.

2.2 Multi-Objective Optimization

The multi-objective optimization approach used is based on the concept of Pareto optimality. It consists in finding the Pareto frontier that is the set of Pareto optimal solutions to the problem, usually referred to as non-dominated solutions, (i.e., solutions for which there is no other solution for improving one objective without degrading at least one other objective). In general, there are multiple Pareto optimal solutions (a set of alternatives with different trade-offs due to conflicting objectives) that form the Pareto frontier (see Fig. 2).

For a solution on this frontier, none of the objectives can be improved without degrading at least one of the others. In practice, usually only one of these solutions is to be chosen. Since Pareto optimal solutions are not ordered (all are equally good considering all criteria together), additional preference information is required to determine a preferred solution.

Multi-objective optimization methods (Miettinen et al. [37]) are often classified according to the decision maker's role in the solution process. Different methods can incorporate the decision maker's preferences before (a priori approach), during (interactive approach), or after (a posteriori approach) having generated the Pareto optimal solutions (see Fig. 3). Three types of preferences can be identified based on trade-off information (e.g., weights for the criteria), reference points (e.g., desired values of criteria), and classification of objective functions.

With the a priori approach (also known as multi-objective mathematical programming), the set of feasible solutions is not explicitly known in advance but is restricted by constraint functions. With the interactive approach, solutions are iteratively improved considering preferences provided by the decision-maker. From a Pareto optimal starting point, new Pareto optimal solutions are iteratively generated, iteratively taking preference information from the decision-maker into account. With the a posteriori approach, there are two tasks: an optimization task that consists of finding Pareto optimal solutions or a representative subset (involving a computer-based procedure) and a decision-making task that consists of choosing a single most preferred solution. After having identified the Pareto frontier (or part of it), an interaction with the decision-maker can make it possible to take his(her) specific preferences into account in order to find the most preferred solution and to learn about the interdependencies of the objectives as well.

The multi-objective optimization approach used in this study is the a posteriori approach using Pareto optimality. A multi-objective optimization problem consists of finding all the non-dominated compromises between the different criteria. We will refer to the points located on this frontier as optimal policies, with acceptable trade-offs, in the sense that there are no other policies that dominate them on every objective.

The problem is to find policies π^* among the given set of possible policies that are non-dominated: $\pi^* \in argmax_{Pareto} \; (f_h(\pi), f_c(\pi), f_b(\pi))$, subject to $\pi \in \Pi$ where Π is the set of every possible policy. We evaluate policies with respect to the three objectives. As discussed in the previous section, when building the Pareto frontier, we restrict ourselves to the $m + 1$ *threshold policies* π_k. The

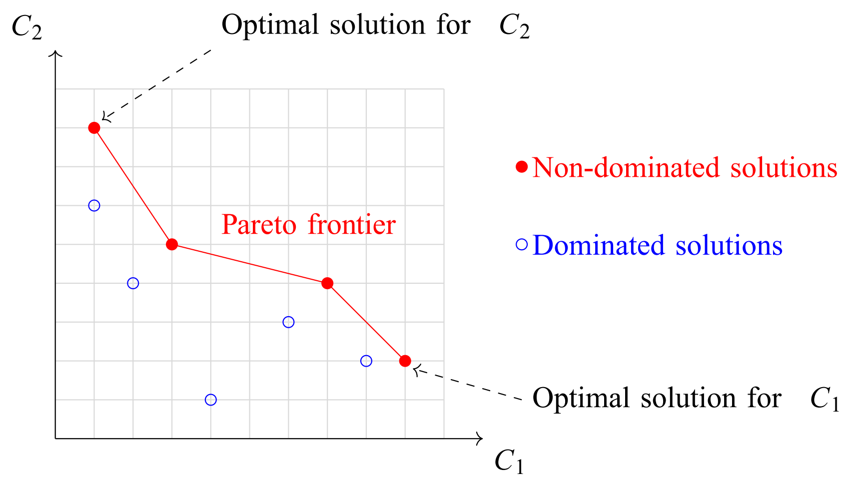

Fig. 2 Example of a Pareto frontier that optimizes two criteria C1 and C2

optimal policies will be those for which the expected values of the criteria are simultaneously non-dominated.

To illustrate the decision-making task, we consider an approach that does not require interactions with the decision-maker (even if it may be more adapted and educational for a specific situation). As suggested by Miettinen et al. [37] to obtain robust solutions, and to involve uncertainties, we then consider the regret value (difference between the chosen decision and the optimal decision) of the decision-maker to not apply the optimal strategy for each criterion (Kouvelis and Yu [33]). The theory of regret aversion or anticipated regret (Mazziotta et al. [36]) proposes that when facing a decision, individuals might anticipate regret and thus incorporate their desire to eliminate or reduce this possibility in their choice. Regret theory models choice under uncertainty, taking the effect of anticipated regret into account. The minimax regret approach is to minimize the worst-case regret.

3 Case Study: Application to a Maritime Pine Stand Facing Fire Risk in Southwestern France

3.1 Model Calibration and Solution Method

The model is parameterized to represent the behavior of a representative NIPF owner producing maritime pine in

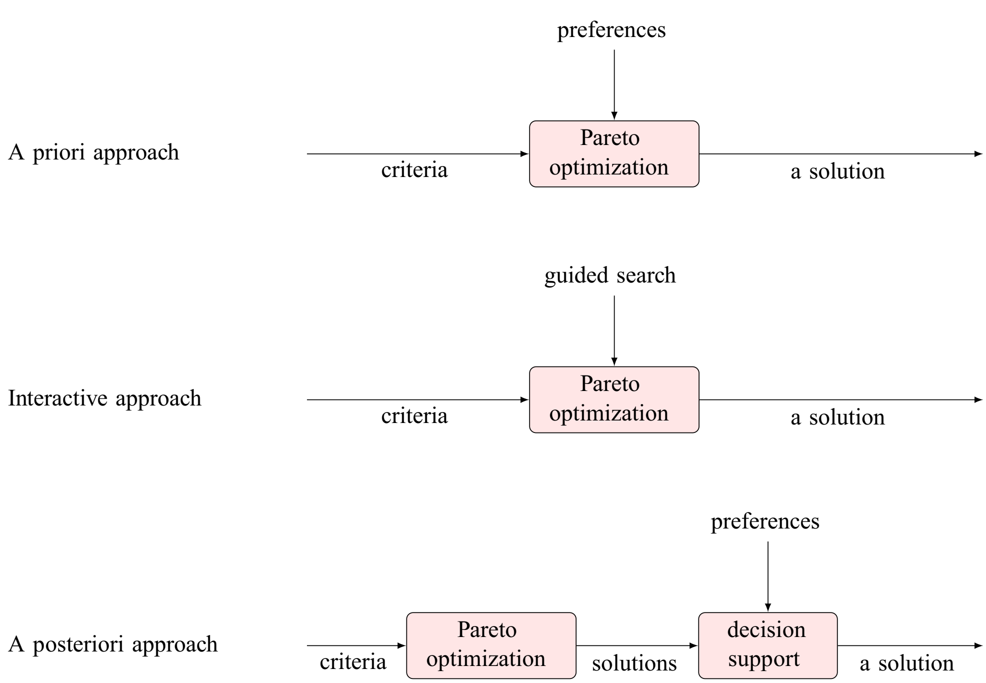

Fig. 3 The three approaches for multi-objective optimization

Table 1 Characteristics of age classes and calibration data

Age class	Timber volume (m^3/ha)	Net price (€/m^3)	Carbon storage (metric tons)	Number of warbler pairs	Biodiversity indicator	Initial probability distribution
1	13.68	7.51	4.10	1.50	0.14	0.12
2	24.53	7.53	7.36	3.87	0.82	0.12
3	43.07	7.63	12.92	4.50	1.00	0.16
4	73.06	7.97	21.92	3.87	0.82	0.12
5	117.50	9.11	35.25	3.00	0.57	0.11
6	175.45	12.04	52.64	2.12	0.32	0.09
7	239.64	16.30	71.89	1.50	0.14	0.05
8	299.05	19.26	89.72	1.12	0.04	0.05
9	345.59	20.42	103.68	1.00	0.00	0.03
10	377.48	20.77	113.25	1.00	0.00	0.15

southwestern France (Aquitaine region).[3] Although the main objective of Aquitaine forests is wood production, non-timber activities are important in this area. Fire is one of the main risks of damage to forests in this area even if many policy measures to control fires are implemented.

Tree growth data, timber use data, and economic data were obtained from the study conducted by Couture and Reynaud [16], and are given in Table 1. We assume that the size of the stand plot is equal to 1 ha (area $= 1$). We consider ten age classes ($m = 10$). At any decision time represented by a 5-year interval, the stand is in one of these age classes. As indicated by Couture and Reynaud [16], the annual probability of fire risk is 0.17% for the selected region. In Aquitaine, fires have burned an average of 3200 ha per year over the period 1981 to 2003, representing roughly 0.17% of Aquitaine's forest area (1,890,481 ha). Moreover, as Vogel [59] points out, the burned areas have been maintained in Aquitaine. We therefore consider that the annual probability of fire risk in Aquitaine is $p_a = 0.17\%$. Additionally, the planting cost, C_p, is estimated at €1000/ha. The salvage proportion, α, is assumed to be 0.1. The value of the discount rate is set to reflect at least the time preference of the NIPF owner: 2% (Gosselin et al. [25]; Brunette and Breda [7]). Based on data provided by the NFI,[4] the probability distribution over the initial states of the system for the considered area is defined in Table 1.

As shown in Table 1, carbon storage in standing trees is directly obtained from the timber volume using the conversion factor λ, fixed to 0.3 (Couture and Reynaud [16]). Biodiversity conservation is modeled using a representative bird species: the warbler (Ferry [22]). The dynamics of presence and evolution of this species depends on the characteristics and condition of the forest, as indicated in Table 1. In the case of clear-cut, since the decision period is assumed to be equal to 5 years, a few birds are able to come back (Nghiem [39]), justifying that the number of warbler pairs is always positive. The distribution of these bird pairs of the species allows us to calculate a normalized indicator of biodiversity in order to have a neutral scaled measure between 0 and 1 (Table 1). Such an indicator allows us to remove the unit of measurement and make the indicators more easily comparable. The normalized indicator $D(s)$ is defined as:

$$D(s) = \frac{N(s) - \underset{s \in S}{Min}\ N(s)}{\underset{s \in S}{Max}\ N(s) - \underset{s \in S}{Min}\ N(s)} \qquad (12)$$

with $N(s)$ the number of pairs for the age class s.

The MDPtoolbox (Chadès et al. [12]) provides functions to evaluate policy.[5]

3.2 Results and Discussion

In this section, after presenting the optimal policy in each of the three models separately, we present the Pareto optimal solutions. We then investigate how fire risk probabilities impact the optimal forest owner decisions and the Pareto frontier.

3.2.1 Optimal Policies for Timber Production, Carbon Sequestration, and Biodiversity Conservation

Figure 4 shows the optimal policies associated with each of the three objectives.

[3] The model could be applied to any other forest species or area by simply modifying the parameters for all of the functions specified.

[4] The National Forest Inventory (NFI)'s purpose is to *describe the surface of the national territory and the occupation of its soil, of elaborating and updating the permanent inventory of national forest resources* (see https://inventaire-forestier.ign.fr/). It provides personalized data tables for specific queries that are useful for our purpose.

[5] All the Matlab codes to run and to reproduce the study are available on the on-line repository FigShare at the following address: https://doi.org/10.6084/m9.figshare.7707233.v2

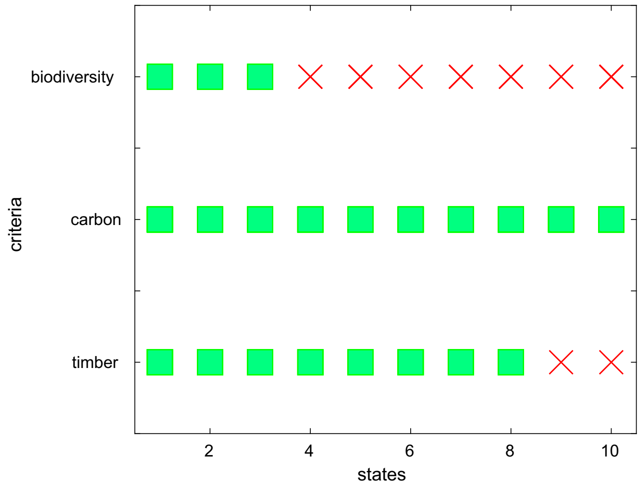

Fig. 4 Single optimization: optimal policies for timber production, carbon sequestration, or biodiversity conservation (green square, wait; red cross, cut)

Fixing a MDP policy defines a Markov chain over the problem states. The corresponding stationary distribution of this Markov chain indicates the proportion of time spent in each class (see Fig. 5).

In the timber production model, we can see in Fig. 4 that for the age classes 1 to 8, it is always optimal not to cut the trees in the plot; the optimal action for these age classes is to wait. In contrast, it is optimal to harvest for the age classes 9 and 10. Figure 5 shows that, for the timber production model, the percentage of time spent in the age classes 1 to 9 is around 0.1 and no time is spent in age class 10. This means that in most cases, the stand will reach state 9 before cutting.

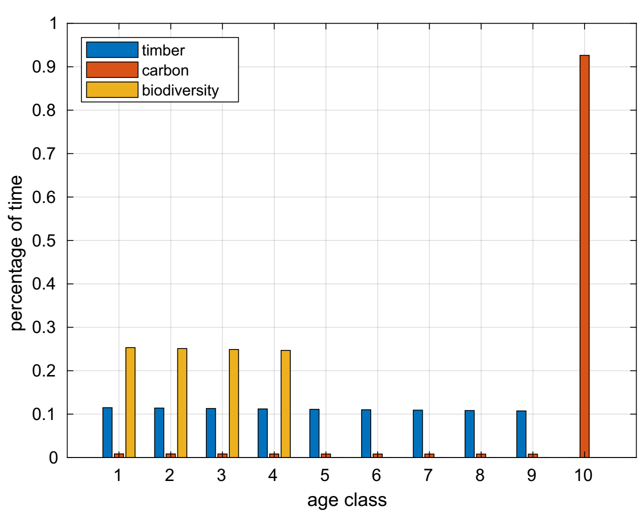

Fig. 5 Percentage of time spent by the stand in each age class for optimal policies obtained for timber production, carbon sequestration, or biodiversity conservation

In the carbon sequestration model, it is always optimal not to cut for every age class as seen in Fig. 4. The optimal policy is to never harvest the trees. We observe that the percentage of time spent in the age classes 1 to 9 is around 1% and the percentage of time spent in the age class 10 is more than 90%. It should be noted that the time spent in the mature age class is greater than in the other age classes, and that the percentages of time spent in these age classes are similar even if they are low.

In the biodiversity conservation model, as we can see in Fig. 4, the optimal policy is to wait in age classes 1 to 3 and to harvest age classes 4 to 10. In Fig. 5, we see that the percentage of time spent in age classes 1 to 4 is 25%, whereas it is null for age classes 5 to 10.

We can note that the optimal policies for the three models are conflicting because different actions may be prescribed for some age classes. Indeed, for age classes 1 to 3, the optimal decisions for the three models are identical, whereas for age classes 4 to 10, differences in optimal decisions appear. For age classes 4 to 8, the biodiversity conservation objective conflicts with both timber production and carbon sequestration objectives. For age classes 9 to 10, timber production and biodiversity conservation objectives appear to be in conflict with the carbon sequestration objective.

The expected values for the optimal policies obtained for each objective are given in Table 2.

3.2.2 Pareto Frontier

Table 3 shows the expected present value for the timber objective and the expected values for the carbon and biodiversity objectives for the non-dominated policies.

Figure 6 is a graphical representation of the Pareto frontier showing optimal solutions in a three-dimensional representation (see Table 3 for a definition of policy labels). This figure provides the optimal policies located on the Pareto frontier that offer compromises between the three objectives. Eight optimal policies are on this frontier, offering a variety of optimal choices for the forest owner. The optimal policies obtained for each objective separately (optimal policy 9 for timber, optimal policy 11 for carbon, and optimal policy 4 for biodiversity) are located on the Pareto frontier. Comparing all optimal policies on the Pareto frontier, a strong gap between optimal policy 11 (never

Table 2 The expected values for the optimal policies computed for the timber, carbon, and biodiversity objectives

Objective	Value	Unit
Timber production	6838	€/ha
Carbon sequestration	108	tons/ha
Biodiversity indicator	0.7	Index

Table 3 Values for the timber, carbon, and biodiversity objectives for the optimal policies belonging to Pareto frontier

Policies (forest management)	Timber revenues (€/ha)	Carbon sequestration (tons/ha)	Biodiversity indicator (between 0 and 1)
4 (to cut from age class 4)	643	11	0.7
5 (to cut from age class 5)	1740	16	0.7
6 (to cut from age class 6)	3243	22	0.6
7 (to cut from age class 7)	5170	29	0.5
8 (to cut from age class 8)	6496	36	0.5
9 (to cut from age class 9)	6838	44	0.4
10 (to cut the age class 10)	6573	50	0.4
11 (never cut)	−92	108	0.0

cut) and all the other optimal policies is observed in the sense that, for policy 11, only a positive but high value for carbon is obtained, whereas for all the others, all three values are positive. A forest management policy maximizing the carbon objective will provide poor results for the other objectives. In our case, longer rotations could be beneficial for carbon storage and timber revenue, reflecting moderate conflicts between timber and carbon objectives, but not for biodiversity conservation. Indeed, conflicts between biodiversity and the other two criteria are strong. This result depends on our choice of a biodiversity conservation indicator based on the requirements of a middle-aged forest for the bird species. On the contrary, it was found in the existing literature (Trivino et al. [57]) that the relationship between carbon storage and biodiversity is generally positive, resulting in low levels of conflict. As a consequence, our work shows that it is not possible to have a high level of biodiversity when carbon storage is maximized.

The great difficulty for the forest owner remains to choose a policy among the different non-dominated policies (acceptable trade-offs) located on the Pareto frontier. In order to have a better representation of the differences between the non-dominated policies, and to analyze the different trade-offs between the different objectives, it is possible to look at the Pareto frontier for every pair of objectives. Figure 7 shows Pareto frontier considering pairs of criterion. It more clearly highlights the potential conflicts between the different policies for the different objectives. According to Mazziotta et al. [36], the notion of conflict arises when comparing various Pareto non-dominated solutions for which the improvement of one objective can be attained only to the detriment of other objectives.

As in Mazziotta et al. [36], based on the regret theory, it is possible to find a Pareto solution representing a good compromise, relative to the forest owner's preferences (see Table 4).

Using an approach based on regret, our principle consists of finding a Pareto non-dominated solution whose cumulated regrets of all values with respect to the corresponding maximal value is minimal. Optimal policy 8 (cut at age 8) represents a good compromise for which the values of all the objectives are positive. In this case, it is optimal to

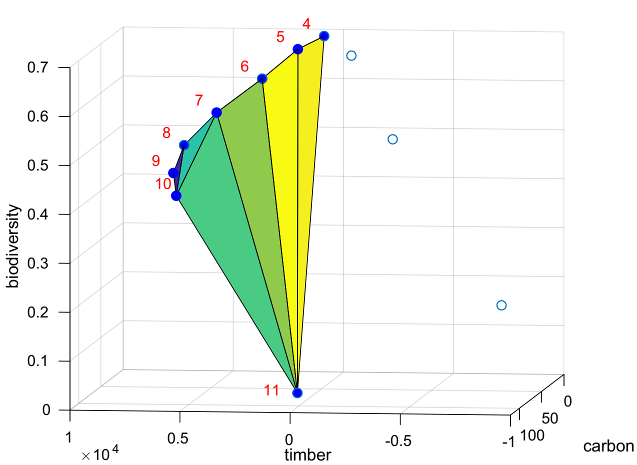

Fig. 6 Pareto optimal solutions: three-dimensional representation of the three objectives

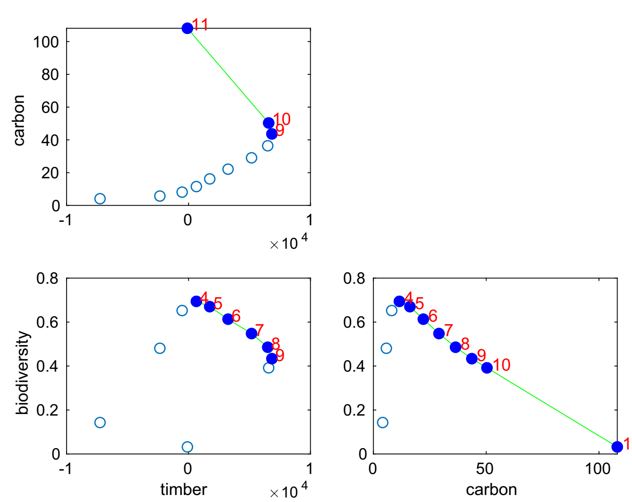

Fig. 7 Triangular set of diagrams for the Pareto fronts of the given binary pairs of objectives (full circle, non-dominated policies; empty circle, dominated policies)

Table 4 Evaluation of regrets for Pareto solutions (obtained for an annual fire probability equal to 0.17%)

Policies (forest management)	Regrets*			Sum of regrets
	Timber revenue	Carbon sequestration	Biodiversity indicator	
4 (to cut from age class 4)	0.906	0.898	0.000	1.804
5 (to cut from age class 5)	0.746	0.852	0.000	1.597
6 (to cut from age class 6)	0.527	0.796	0.143	1.466
7 (to cut from age class 7)	0.244	0.731	0.286	1.261
8 (to cut from age class 8)	0.050	0.667	0.286	1.002
9 (to cut from age class 9)	0.000	0.593	0.429	1.021
10 (to cut the age class 10)	0.039	0.537	0.429	1.004
11 (never cut)	1.013	0.000	1.000	2.013

*Regrets are evaluated as $\frac{Max f_X(\pi) - f_X(\pi)}{Max f_X(\pi)}$

harvest for age class 8 in order to obtain timber revenue equal to €6496/ha, carbon storage totaling 36 tons, and a biodiversity indicator of 0.5.

The information provided in Table 3 can also be used to define incitative public policies that take forest ecosystems into account. Since the way a forest is managed can influence carbon sequestration or biodiversity conservation, forest management practices targeted toward such objectives are costly. Indeed, as an example, this Pareto frontier may be useful to assess private forest owner's losses due to changes in forest management practices in order to take account of carbon sequestration and biodiversity conservation objectives, and to then determine the compensation necessary to pay for reducing rotation length. Such compensation is simply equal to the difference between the expected values for these two policies. A biodiversity conservation program that includes biodiversity conservation and enforces the age of cutting to the age class 7, for example, should be implemented only if this program provides subsidies to the forest owner to compensate for the decrease in timber revenues (the loss from policy 9 to policy 7 is equal to €1668/ha, carbon storage drops by 11.3 tons, but the biodiversity indicator rises by 0.1).

3.2.3 Assessment of the Risk Impact on the Pareto Frontier

Natural disturbances affect the dynamics of ES, and are expected to increase with climate change (Seidl et al. [52]). An increasing trend in fire frequency is not guaranteed for the studied area, principally due to the lack of data and studies. However, it is still assumed that climate change and increased climate variability are expected to have impacts on fire occurrence probabilities. For forest owners, it is believed that adapting to climate change will require major adjustments in management practices. This is why we now investigate the impact of an increase in the fire risk probability on the forest management model, and on the non-dominated solutions. We therefore consider that the impact of climate change is taken into account by solving different MDP with different fire risk probabilities. It is usual and relevant in the literature to model climate change through a change in fire occurrence, since there is no exact prediction of its impact on forest ecosystems (Schou et al. [50]).

In addition to the initial value of fire risk probability, we consider another value (an annual probability of fire $p_a = 1.7\%$, inducing a probability of fire for the period $p_f = 8.22\%$) that corresponds to a tenfold increased annual fire risk. As we can see in Fig. 8, an increase in fire risk does not have much impact in terms of non-dominated policies, and does not affect the number of non-dominated solutions located on the Pareto frontier. This can perhaps be explained by the still relatively small values considered for fire risk probability. Although the shape of the Pareto frontier remains roughly unchanged, the expected present values for the optimal policies obtained for the non-dominated solutions located on the Pareto frontier are strongly reduced. An increase in the probability of fire risk will result in a decrease in the expected present value of the policies (see Table 5). The expected present value should decrease since a higher proportion of timber might be damaged by fire when the fire risk probability is increased. Obtained using the same regret-based approach, a good compromise with positive values for all objectives now corresponds to optimal policy 9 (cut at age 9) located on the Pareto frontier. This later age cutting results from the rise in biodiversity values for the highest age classes.

If, as previously analyzed, a biodiversity conservation program designed to enforce the age of cutting from the age class 7 is implemented, then the necessary subsidies for compensating for the decrease will be halved and only equal to €886/ha in this new risk context (with a decrease of 14.5 tons for carbon storage and a rise of 0.1 for biodiversity).

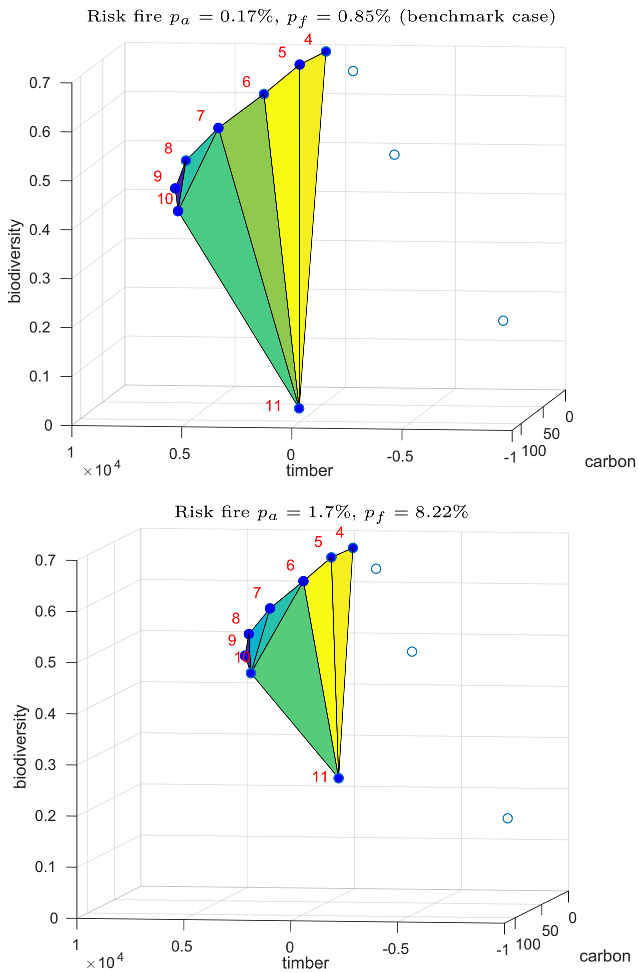

Fig. 8 Assessment of the risk impact on the Pareto frontier

3.2.4 Discussion and Limitations

Our approach provides new insights into forest management under risk taking conflicting objectives provided by forest ecosystems into account, and demonstrating the utility of using a multi-objective optimization approach, as well as the use of MDP for modeling the problem of forest management under risk. Indeed, MDP models combined with the Pareto frontier allow us to obtain solutions for multicriteria forest management problems under risk. The optimal policy obtained from MDP is deterministic; there is one single optimal decision for each state of the forest, rendering the policy easy to implement. The Pareto frontier represents the different non-dominated solutions for the problem of the multi-objective optimization under risk. The essence of our approach is to impose no constraints, and to consider undiscounted and discounted criteria simultaneously. For efficient multicriteria forest management under risk, it is fundamental to consider the different criteria in their appropriate-measure and magnitude. All criteria, discounted and undiscounted, are measured with suitable units but are not directly comparable and may be conflicting. For example, the provision of biodiversity may compete with the provision of timber. Without setting any target level or any constraints for each objective, we simultaneously deal with ecosystem service, biodiversity, and economic objective and obtain optimal solutions with guaranteed Pareto efficiency. All the Pareto optimal solutions are considered desirable and can be potentially chosen by the forest owner. Finding the most preferred solution requires trade-offs between criteria and further clarification about the forest owner's preferences. After having generated the Pareto optimal solutions, we can incorporate the forest owner's preferences to identify the most preferred one among them (here a regret approach but may be an other one). The benefit of this a posteriori approach is that it makes it possible to use desirable objective function values rather than more abstract weighting, when evaluating solutions, ensuring a Pareto optimal solution (rather than satisfactory solution often obtained when using goal programming). Despite the absence of weighting, this study highlights the importance of knowing the forest owner's preferences in practical situations. It is the

Table 5 Values and regrets for the timber, carbon, and biodiversity objectives for the optimal policies belonging to Pareto frontier (obtained for an annual fire probability equal to 1.7%)

Policies	Timber revenues		Carbon sequestration		Biodiversity indicator		Sum of regrets
	Values (€/ha)	Regrets	Values (tons/ha)	Regrets	Values	Regrets	
4	−189	1.028	11	0.898	0.7	0.000	1.926
5	718	0.895	15	0.861	0.7	0.000	1.756
6	1900	0.722	20	0.815	0.6	0.143	1.680
7	3324	0.514	26	0.759	0.6	0.143	1.416
8	4167	0.391	31	0.713	0.5	0.286	1.389
9	4210	0.384	37	0.657	0.5	0.286	1.327
10	3808	0.443	42	0.611	0.4	0.429	1.483
11	−1048	1.153	72	0.333	0.3	0.571	2.058

latter who ultimately chooses the optimal policy to be implemented. Therefore, although there is work to be done one eliciting the forest owner's preferences, either upstream or downstream, our approach for obtaining optimal forest management policies can be seen as an aid for revealing these preferences. Indeed, it allows the decision-maker to evaluate the impact of his or her preferences on the optimal policy to be implemented. For example, some owners assign greater value to economic factors, whereas some owners residing in urban spaces are more sensitive to the ecological factor. These differences in forest values condition the choice of the optimal forest management policy. The Pareto frontier gives optimal forest management plans for these different types of forest owners. More recently, some studies have observed that multi-objective owners were an important type of NIPF owner, for whom economic as well as ecological benefits are all very important and equally valued (Haugen et al. [27]; Côté et al. [14]). In this case, the Pareto frontier obtained delivers helpful information to this type of forest owner for selecting optimal forest management practices.

Moreover, our approach may help governments to implement public policy involving the ES of the forest and to induce a change in some forest owners' behaviors. Although some NIPF owners consider all the different services provided by the forest, many often consider only the timber production service. The major role of forests in mitigating climate change, through carbon storage, and its importance in conserving biodiversity may also be considered public goods. Public authorities can implement public aid programs to induce NIPF owners to consider them. The approach proposed here and its outputs would make it possible to evaluate the difference in values obtained with or without considering ES and biodiversity. Governments could then calculate the amounts of aid or subsidy to be allocated for the consideration of these services by all types of NIPF owners without impacting their well-being. Our approach makes it possible to identify the highest levels achieved by all the different criteria for all the optimal Pareto solutions, and to select the corresponding optimal policies. Governments can then implement incentives for NIPF owners to choose these optimal policies.

In the same way, our approach is a useful tool for global investigation and study of climate change. The overall effects of this change are measured in terms of timber, carbon, and biodiversity as well. Adapting to climate change for NIPF owners will require major changes in their forest management practices. As indicated, it is useful to study the impact of an increase in the fire probability on optimal policies for multicriteria forest management to obtain this adaptation. We have illustrated this principle by solving the MDP model with a high probability. This value is considered to be strong by experts, in any case, considering it allows us to study the effect of climate change on optimal forest management policies as well as to assess the amount of potential prevention actions that should be implemented to affect this probability. The framework proposed would also make it possible to test different scenarios of climate evolution through changes in probabilities.

However, in our approach, the biodiversity indicator definition strongly impacts the optimal solution set. Since biodiversity is measured by an index according to the characteristics of the forest, the relationship clearly shows the impact it will have on the definition of optimal forest management policies. Such an index depends on a multitude of factors other than the forest that would need to be considered. This would require additional work in itself.

Moreover, the economic criterion used here is the discounted criterion, as advocated by economics, but without considering risk aversion. The risk preferences of the forest owner are not considered, even though it is increasingly accepted that NIPF owners are risk-averse (Buongiorno et al. [11]; Brunette et al. [8]; Zhou and Buongiorno [62]). This aspect should be taken into consideration in the MDP model using different approaches to best describe the behavior of NIPF owners (Couture et al. [15]). This is a subject for future research and not within the scope of our study.

4 Conclusion

We developed a multiple objective forest management model to study the interactions of timber production and biodiversity conservation as well as carbon sequestration in a forest ecosystem under fire risk. Our approach is based on the concept of Pareto optimality and on the use of MDP for modeling the problem of sequential forest management under risk. Pareto optimality provides a methodology that incorporates competing objectives and provides decision-makers with multiple alternatives of optimal forest management policies, taking different objectives into account.

An application of our model is provided for maritime pine production in southwestern France. Our results show that it is very difficult to simultaneously maintain high levels of timber and non-timber objectives. Although a globally optimal policy that simultaneously maximizes all the objectives does not exist, it is possible to find forest management trade-offs to effectively consider the three forest ES. Indeed, with acceptable trade-offs, it is possible to greatly increase non-timber objectives. The preferences, however, have to be discussed by forest owners in order to choose the policy to be implemented. Our study could also be used by decision-makers to evaluate the use of public policies to enforce the consideration of various objectives.

Consequently, this research demonstrates that the combination of MDP and the Pareto frontier may help to overcome constraints to adapting forest management to the provision of forest ES. It provides information settings where decision-makers may select optimal policies that ensure acceptable forest management that targets the provision of ES.

This research could be extended in additional directions. First, since forest owners are generally recognized as risk-averse, future research should attempt to include risk aversion, as proposed by Couture et al. [15], who present a method for integrating risk aversion into a MDP framework.

We could then consider multistand forest management problems (or uneven-aged stands, which is similar). Considering multiple stands in forest management is a hard computational problem (Couture et al. [15]; Forsell et al. [24]). Couture et al. [15], for example, proposed an exact *state aggregation* method that allowed to optimally manage (using a single-criterion) forests with 12 stands and 5 age classes, using MDP. Approximate methods in Forsell et al. [24] allow managing forests with more than hundred stands, allowing fine-grained MDP management of uneven-aged forests under a single criterion. Incorporating multiple criteria forest management with uneven-aged forest management would generate several difficulties. Policies may be efficiently evaluated along the different criteria; however, the exploration of the full policies set may be far too costly. However, there exist several approaches to multi-criteria MDP, which exploit dynamic programming approaches to construct the Pareto front (White [60]; Krishnendu et al. [34]; Wiering and de Jong [61]). Alternately, since evaluating any policy along the different criteria is easy, we could also use general purpose Pareto-frontier exploration approaches (Figueira et al. [23]).

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