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Balancing forest profitability and deadwood maintenance in European commercial forests: a robust optimization approach

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Abstract

This study seeks to include two central aspects of forest management into an optimized forest planning model for commercial European forests: (i) the uncertainty related to climate change and forest responses to new environmental conditions and (ii) the maintenance of deadwood on forest stands, essential for sustaining biodiversity and promoting forest resilience. We analyzed forest outcomes of alternative management regimes generated by the process-based model 4C, considering four climate change scenarios. We evaluated the impacts on forest economy caused by an increasing amount of deadwood biomass left on forest stands, applying a deterministic and a robust forest planning model. Our results show that areas with high growth rates and low wood prices display the lowest trade-off between profitability and deadwood maintenance, whereas regions with high wood prices display high opportunity costs for maintaining large amounts of deadwood. Moreover, selecting robust management regimes caused minor impacts on the NPV, with an average reduction of 7% compared to the deterministic optimal solutions, appearing as a suitable alternative for integrating climate uncertainty into forest management planning.

Keywords Forest management · Biodiversity · Deadwood · Uncertainty · Robust optimization · Forest planning

Introduction

Accounting for climate change impacts on forest ecosystems is essential for achieving sustainable forest management, acting to mitigate negative impacts on forest functions, while benefiting from potential positive stimuli in forest productivity (Bolte et al. 2009; Cheaib et al. 2012; Lindner 2000). Although accurate information regarding climate change is still lacking, it is advisable that forest managers act in advance because the long life span of trees may mean that responses to new conditions will be potentially slower than climatic changes (Lindner et al. 2010; Spittlehouse and Stewart 2004). Moreover, it is crucial to increase resilience of forests to prevent the development of ecosystems to undesirable states resulting from climate pressures (Temperli et al. 2012).

Several management strategies for coping with climate change at stand and landscape scale have been proposed in the literature (Heller and Zavaleta 2009). Forest management can play an important role in enhancing the adaptive capacity of forests, reducing risk of economic and environmental damage (Bolte et al. 2009). Particularly, modifications of thinning regimes, rotation length and species composition may contribute to the maintenance of ecosystem functioning in European forests (Kolström et al. 2011; Schelhaas et al. 2015). For example, increasing thinning intensity may improve water availability for the remaining stand and speed up its recovery after drought events, while increasing forest profitability in areas with positive response to climate change (D'Amato et al. 2013, Kohler et al. 2010).

The maintenance of ecosystem functioning under climate change, however, requires a multipurpose forest management approach, and it is key that forest managers integrate forest biodiversity goals when deciding upon alternative management regimes under climate change. Biodiversity may enhance forest resistance and resilience under

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environmental pressures (Isbell et al. 2015; Thompson et al. 2009) and act as an insurance for ecosystem functioning in the future (Baumgärtner 2007). Nevertheless, forest management has severely compromised the habitat of several forest taxa in Europe, especially for saproxylic organisms. These organisms are dependent on deadwood in at least one stage of their life, and they represent an important share of forest biodiversity, playing a key role on nutrient cycling (Gossner et al. 2013). Assessments in European forests indicate that deadwood volumes are considerably low for managed stands, with an average of 11.5 m^3/ha, compared to the amounts found in forest reserves, ranging from 59 to 216 m^3/ha (Hahn and Christensen 2005; MCPFE 2015). The provision of deadwood in forest stands must also take into account the impacts of climate change and management on deadwood dynamics, since they directly affect deadwood supply through alterations on decay rates, mortality rates and inter-tree competition (Zell et al. 2009).

One major challenge for management planning under climate change is to quantify the expected impacts of climate drivers on forest dynamics and the uncertainty related to future climate development. Process-based forest growth models provide an opportunity for managers to identify trends and ranges of forest development under novel climatic conditions, through testing a variety of different climate change and forest management scenarios (Lindner et al. 2010). This makes it possible to assess the behavior of certain variables such as forest productivity and carbon balance under different climate change paths and support decision making. However, this information alone might not suffice for forest managers, as we are still unable to accurately assign probabilistic weights to different climate change scenarios (Yousefpour and Hanewinkel 2016). Hence, there is a need to identify management options yielding suitable and stable responses regardless of which climate scenario will become true.

Robust optimization (RO) is a suitable tool for addressing problems of this nature. This technique includes the uncertainty of input parameters in mathematical models, identifying robust solutions, i.e., solutions with stable outcomes in the face of parameter fluctuations (Beyer and Sendhoff 2007; Mulvey et al. 1995). This approach has been successfully applied in several natural resources management problems involving uncertainty, such as water management (Cunha and Sousa 2010; Ricciardi et al. 2007; Watkins and McKinney 1997), air quality (Liu et al. 2003) and conservation planning (Augustynczik et al. 2018; Regan et al. 2005). Robust optimization and robust decision making have been recently gaining attention in the forestry literature (Radke et al. 2017). For example, Knoke et al. (2016) applied a robust optimization model for land use planning in a tropical forest landscape. Messerer et al. (2017) developed a robust optimization

model to a forest conversion problem under economic uncertainty, and Kašpar et al. (2017) used robust optimization to find solutions to a harvest scheduling problem under inventory and growth forecast uncertainty.

Because future climate and concurrent forest responses are deeply uncertain, RO has an immediate application for supporting forest planning, allowing for the selection of robust management regimes with stable outcomes under the considered scenarios. Yet, there is a gap in the application and evaluation of this approach to forest management and conservation planning under climate uncertainty. This study proposes to address this issue and has three main objectives: (i) apply deadwood biomass as a biodiversity indicator to a forest planning model and evaluate the capacity of European forests to maintain deadwood in forest stands under changing climate, (ii) assess the impact of the deadwood requirements inclusion on the economic outcomes of different management strategies and (iii) evaluate the performance of a robust optimization model toward climate uncertainty in comparison with deterministic optimal solutions.

To address our objectives, we simulated forest development under climate change using the process-based model 4C and included biodiversity requirements into the optimization model by introducing deadwood constraints. These constraints required a minimum level of deadwood biomass to be left in stands. To include climate change uncertainty into our planning problem, we applied a robust optimization model, selecting the solution that yielded the lowest weighted average of the maximum and minimum economic loss across all climate change scenarios. For economic evaluations, we used the concept of net present value (NPV) by discounting cash flows with a fixed interest rate of 2%. Similar to the deadwood requirements, we analyzed the impacts of selecting a robust solution rather than a deterministic solution on the NPV obtained.

Materials and methods

Data

We used data from 132 plots from the ICP Forests Level II database (http://icp-forests.net/page/level-ii) for the forest simulations. The plots included the five most abundant tree species in Europe (*Fagus sylvatica, Picea abies, Pinus sylvestris, Quercus petraea* and *Quercus robur*) distributed in 18 European countries (details in supplementary 1). For the economic evaluation of our management regimes, we used the prices and costs from the EFISCEN model database to compute the net harvesting revenue for each species (details in supplementary 1) and a 2% interest rate (Hanewinkel et al. 2013).

Forest simulation and economic evaluation

We employed simulations from the forest model 4C in our analysis. 4C is a process-based growth model, capable of simulating forest dynamics, as well as ecosystem water and carbon balance (Lasch et al. 2005) (for a detailed description, see https://www.pik-potsdam.de/4c/). The accumulation of deadwood in the model is driven by mortality and the decomposition rates, which is a function of various climate drivers. The mortality submodel has different components, including ageing, growth suppression, management and disturbances. The probability of mortality increases when the leaf mass reduces in subsequent stress periods, due to water limitations, insufficient light and stand overstocking (Lasch-Born et al. 2015). Here, we do not consider mortality triggered by disturbances.

We considered 64 management regimes for each plot, which were generated by the permutation of four management interventions in three decision points and modifying thinning intensity: (1) no thinning (N); (2) business-as-usual (BAU) thinning, i.e., the thinning regime currently applied; (3) increased thinning intensity (I); and (4) decreased thinning intensity (D). We applied an 80-years simulation period, with management decisions in years 10, 20 and 30, where the thinning intensity selected in year 30 was repeated until the end of the simulation period. These 64 management regimes were simulated under four climate change scenarios, resulting from the combination of three Global Circulation Models/Regional Climate Models and two emission scenarios: CCLM/ECHAM5 (CCLM) for A1B and B1 emission scenarios, HadRM3/HadCM3 (HAD) and HIRHAM3/Arpège (HIR) for A1B emission scenario. Subsequently, we computed the NPV and deadwood biomass generated by each management regime to establish optimal combinations of forest profitability and deadwood maintenance (see details in supplementary 1 and supplementary 2). Finally, the NPV and deadwood biomass at country level was established by weighting the NPV and biomass of the species considered in our study, according to its area in each country.

For calculating the profitability of each management regime, we computed the NPV for the 80-years simulation period. To this end, we considered the standing stock at the beginning of the period as the initial investment and the revenues were given by thinning revenues and the value of the standing stock at the end of the simulation period (details in supplementary 2).

Planning models

ILP optimization model

In order to identify optimal management options, we applied an Integer Linear Programming (ILP) model to maximize the NPV generated by all species and countries, while maintaining deadwood biomass above the specified thresholds, relative to the maximum deadwood production. A description of the input data, sets and variables is provided in Table 1.

$$\text{Max } Z = \sum_{i=1}^{CC} \sum_{j=1}^{SP} \sum_{k=1}^{CT} \sum_{n=1}^{MG} npv_{ijkn} x_{ijkn} \tag{1}$$

$$\sum_{n=1}^{MG} dead_{ijkn} x_{ijkn} \geq \max_{n \in MG} dead_{ijkn} fdead \quad \forall i, \forall j, \forall k \tag{2}$$

$$\sum_{n=1}^{MG} x_{ijkn} = 1 \quad \forall i, \forall j, \forall k \tag{3}$$

$$x_{ijkn} \in \{0, 1\} \quad \forall i, \forall j, \forall k, \forall n \tag{4}$$

The objective function (Eq. 1) maximizes the sum of the NPV generated by each species in each country, under each climate change scenario. Constraint (Eq. 2) is the deadwood maintenance constraint. It enforces that for each climate change scenario, species and country, the deadwood biomass in the stand is above the respective threshold, expressed as a fraction of the maximum deadwood production in the specified climate change scenario, species and country. We solved the model multiple times, with values for fdead ranging from 0 to 1 using an increment of 0.1, enabling to evaluate the sensitivity of the NPV to the increase on the deadwood maintenance requirement. Constraint (Eq. 3) guarantees that for each climate change scenario, species and country, only one management is selected for the solution and constraint (Eq. 4) obliges the decision variables to take binary values.

Robust optimization model

In natural resource management, climate change is a key source of uncertainty, since managers are unable to define accurately the probabilistic distributions for different scenarios. To safeguard our solution against climate change uncertainty, we developed a robust counterpart of our planning problem, applying the regret concept. The regret refers to the deviation in the value of the objective function for choosing a robust solution (more conservative but safer) rather than the deterministic optimum. Our robust model had as an objective the protection of the solution against climate change uncertainty and maintenance of deadwood biomass above the respective thresholds, regardless of the climate trajectory. We optimized the NPV deviations generated by the robust option, compared to the maximum NPV value for each climate change scenario, following the objective function described in Lempert and Collins (2007):

Table 1 Description of the optimization sets, variables and input data

Sets	Description
CC	Set of climate change scenarios
SP	Set of species
CT	Set of countries
MG	Set of management regimes

Variables	Description
x_{ijkn}	Binary variable that takes value $= 1$ if management n is selected for the solution in climate change scenario i for species j in country k or value $= 0$ otherwise
R_{jk}^{best}	Minimum relative deviation of NPV for species j in country k
R_{jk}^{worst}	Maximum relative deviation of NPV for species j in country k
D_{ijk}	Absolute deviation from the maximum NPV obtained for species j in country k under climate change scenario i

Data	Description
npv_{ijkn}	Net present value generated in climate change scenario i by species j in country k, under management regime n
$dead_{ijkn}$	Average deadwood biomass yielded in climate change scenario i for species j in country k, under management regime n
$\max_{n \in \text{MG}} npv_{ijkn}$	Maximum attainable NPV in climate change scenario i for species j in country k
$\min_{n \in \text{MG}} npv_{ijkn}$	Minimum attainable NPV in climate change scenario i for species j in country k
$\max_{n \in \text{MG}} dead_{ijkn}$	Maximum attainable average deadwood biomass produced along the simulation period, in climate change scenario i for species j in country k
$fdead$	Fraction of the maximum deadwood production
z	Weighting constant

$$\text{Min } Z = zR_{\text{best}} + (1 - z)R_{\text{worst}} \qquad (5)$$

The robust objective function (Eq. 5) minimizes a weighted average of the minimum and maximum deviations from the baseline (regret) related to the parameter fluctuation. The constant z controls the relative importance of minimum and maximum regrets. If we define a small value for z, more importance is allocated to the worst case, yielding a more conservative solution. According to Lempert and Collins (2007), this formulation shows some advantages, as it preserves the ordering and can be reduced to the min–max decision criteria (if $z = 0$), as well as being applied to a variety of models with different levels of complexity.

Applying these concepts to the ILP model detailed in the previous section, we introduce the following robust formulation (for a description of variables, sets and input data, see Table 1):

$$\text{Min } Z = \sum_{j=1}^{\text{SP}} \sum_{k=1}^{\text{CT}} \left(zR_{jk}^{\text{best}} + (1 - z)R_{jk}^{\text{worst}} \right) \qquad (6)$$

$$\sum_{n=1}^{\text{MG}} npv_{ijkn} x_{ijkn} + D_{ijk} = \max_{n \in \text{MG}} npv_{ijkn} \quad \forall i, \forall j, \forall k \qquad (7)$$

$$R_{jk}^{\text{best}} = \min_{i \in \text{CC}} \left\{ \frac{D_{ijk}}{\max_{n \in \text{MG}} npv_{ijkn} - \min_{n \in \text{MG}} npv_{ijkn}} \right\} \quad \forall j, \forall k \qquad (8)$$

$$R_{jk}^{\text{worst}} = \max_{i \in \text{CC}} \left\{ \frac{D_{ijk}}{\max_{n \in \text{MG}} npv_{ijkn} - \min_{n \in \text{MG}} npv_{ijkn}} \right\} \quad \forall j, \forall k \qquad (9)$$

$$3x_{1jkn} - x_{2jkn} - x_{3jkn} - x_{4jkn} = 0 \quad \forall j, \forall k, \forall n \qquad (10)$$

$$\sum_{n=1}^{\text{MG}} dead_{ijkn} x_{ijkn} \geq \max_{n \in \text{MG}} dead_{ijkn} fdead \quad \forall i, \forall j, \forall k \qquad (11)$$

$$\sum_{n=1}^{\text{MG}} x_{ijkn} = 1 \quad \forall i, \forall j, \forall k \qquad (12)$$

$$x_{ijkn} \in \{0, 1\} \quad \forall i, \forall j, \forall k, \forall n \qquad (13)$$

The objective function (Eq. 6) minimizes the weighted sum of the minimum and maximum regrets for all countries and species included in our study. We define the weighting factor z, equal to 0.5, thus assigning equal importance to both minimum and maximum regrets, balancing optimality and robustness. Constraint (Eq. 7) relates the NPV deviation of each country and species, under each climate change scenario, as the NPV reduction compared to the maximum NPV. The maximum NPV and deadwood biomass values were established a priori and used as input data in our model. Constraint (Eq. 8) assigns the minimum regret as the minimum relative NPV deviation of a management regime

among the four climate change scenarios. Similarly, constraint (Eq. 9) assigns the maximum regret as the maximum relative NPV deviation among all climate change scenarios. Both constraints were linearized by introducing an auxiliary variable and scaled by the normalization parameters in the denominator. The normalization parameters express the range of NPV (maximum NPV–minimum NPV) across all management regimes, for a defined species, country and climate change scenario, and are applied in order to evaluate the NPV differences between climate change scenarios in the same scale. Constraint (Eq. 10) requires that for a defined species and country, the same management regime is selected for all climate change scenarios. The set of constraints (Eqs. 11–13) is the same set of constraints (Eqs. 2–4) detailed in the previous section. We generated the NPV and deadwood biomass for each country as an average of the outputs for each species in the considered country, weighted by the forest area of the different species (see supplementary 1).

Results

Deadwood maintenance

The maximum deadwood biomass production varied among the considered countries (Fig. 1). Scandinavian countries had a generally lower capacity for deadwood production. For example, Finland and Estonia showed an average deadwood biomass of 26.2 and 27.6 t DW/ha,

respectively. The highest deadwood biomass production was observed in Austria, Poland and Slovakia, showing an average biomass of deadwood above 110 t DW/ha. The remaining Central European countries displayed similar patterns with maximum deadwood production ranging from 50 to 80 t DW/ha. We highlight that our simulations did not consider the existing deadwood on forest stands, and therefore the reported amount refers to the maximum deadwood produced by applying no management. In our analysis, deadwood accumulation was driven by inter-tree competition and background mortality (age related). In this sense, countries with faster growing, denser and older forests in Central Europe (e.g., Germany and Switzerland) displayed higher deadwood biomass, whereas countries in Scandinavia showed lower deadwood accumulation, due to the lower deadwood input.

We perceived an effect of climate on the deadwood maintenance period. Figure 1 shows the average accumulation of deadwood biomass in each country included in our analysis. Climate directly affects forest productivity and ecologic processes, modifying mortality rates and deadwood production. Moreover, decay rates also depend on temperature and precipitation, thus being affected by climate change. The highest deadwood production occurred under the HAD A1B scenario, especially in Central Europe, with an average deadwood production 17% higher compared to the remaining climate scenarios. The HIR A1B scenario showed intermediary values, and deadwood production was lower under the CCLM A1B and CCLM B1 scenarios.
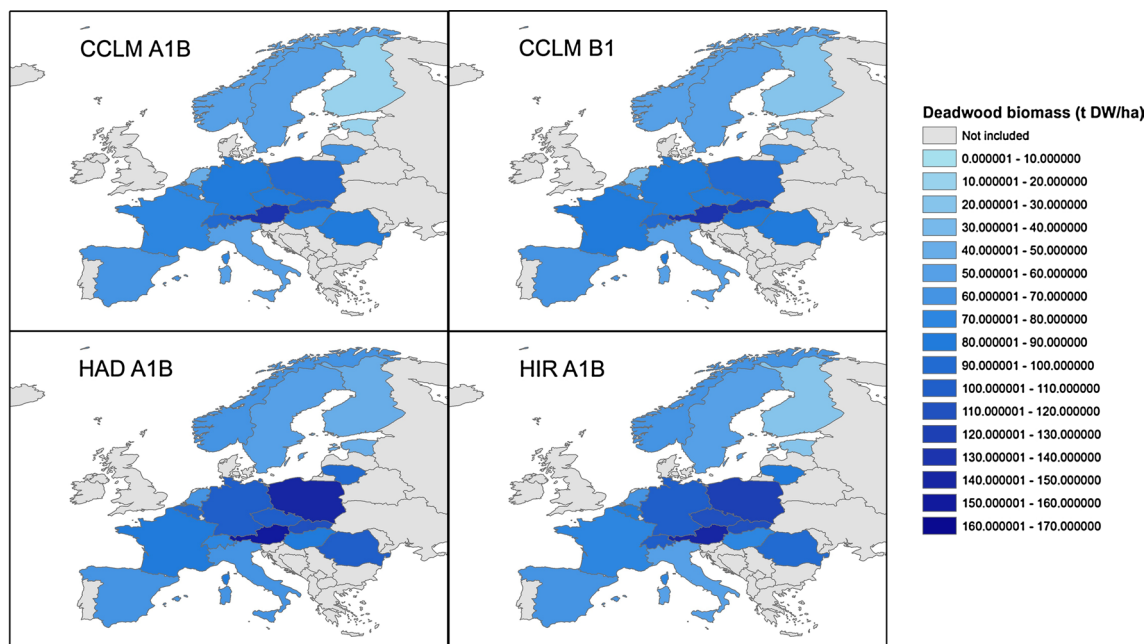

Fig. 1 The figure shows the maximum deadwood biomass production for each country included in our study, as an average along the simulation period and for each climate change scenario considered
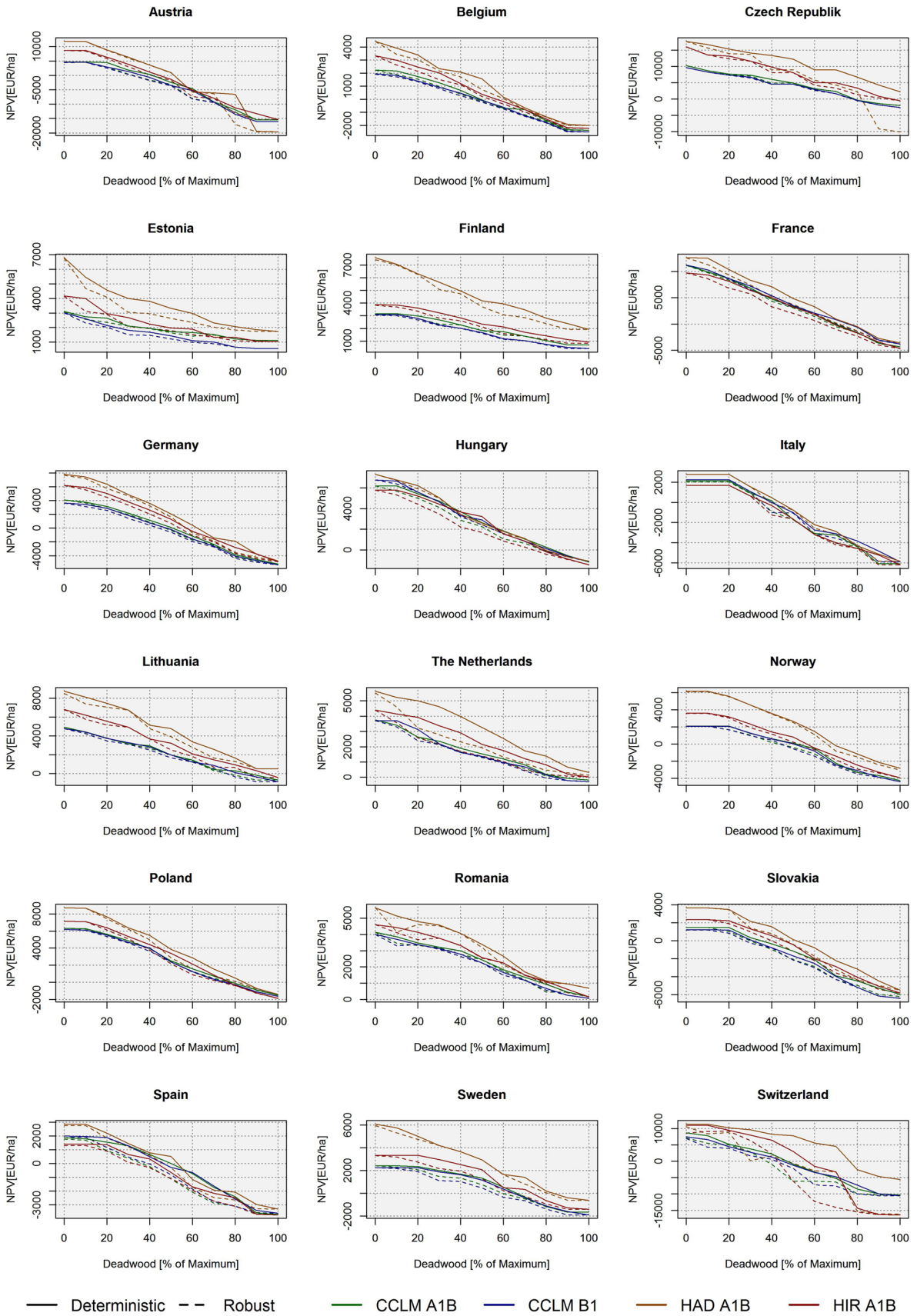
Austria, Belgium, Czech Republik, Estonia, Finland, France, Germany, Hungary, Italy, Lithuania, The Netherlands, Norway, Poland, Romania, Slovakia, Spain, Sweden, Switzerland — NPV[EUR/ha] vs Deadwood [% of Maximum]. Legend: Deterministic, Robust, CCLM A1B, CCLM B1, HAD A1B, HIR A1B

◄**Fig. 2** The figure shows the deterministic and robust NPVs with increasing deadwood production requirements. The colors refer to each climate change scenario considered, the solid lines show the deterministic solutions and the dashed lines show the robust solutions

Economic implications

Analogously to the deadwood volume maintenance, the NPV varied significantly among countries. The maximum NPV of European countries, obtained without the inclusion of deadwood requirements, ranged from €1212.18/ha to €17,719.52/ha, with an average of €5181.11/ha. Central European countries had the highest profitability during the simulation period, especially in Austria, Czech Republic, France and Switzerland (maximum NPV equal to €7431.1/ha, €13,422.9/ha, €11,207.97/ha and €9610.1/ha, respectively). On the other hand, Italy, Slovakia and Spain showed the poorest economic outcomes, with maximum NPV equal to €2221.97/ha, €2178.81/ha and €2024.92/ha on average for the four climate change scenarios (Fig. 2). The differences of NPV among the countries included in our study resulted from variations in forest growth rates, wood prices and species composition. Countries in Central Europe showed higher growth rates and wood price, resulting in increased forest profitability. Conversely, Scandinavian countries and countries with large share of *Fagus sylvatica* in our dataset showed lower profitability, due to the slower growth rates and low wood prices.

The inclusion of deadwood requirements led to a strong NPV reduction for thresholds above 20% of the maximum deadwood (under no management). In general, it was possible to promote deadwood on forest stands with moderate NPV losses for countries with lower wood prices (Estonia and Finland) and high growth rates (Czech Republic and Romania). Conversely, countries with high wood prices and moderate growth rates in Central Europe showed a strong trade-off between profitability and deadwood maintenance, especially under high deadwood maintenance requirements (e.g., France and Austria). In Mediterranean areas, a deadwood biomass requirement of 40% of the maximum (23 and 26 t DW/ha) led to the economic infeasibility of forest management (NPV < 0). We highlight here that typical thresholds for deadwood found in the literature (20–50 m^3/ha) would be achieved with low cost, as they represent 2–25% of the maximum deadwood production (considering a deadwood density of 0.4 t/m^3). Hence, it is possible to promote biodiversity and multifunctionality of European forests with reasonable costs for forest owners.

The climate change trajectory had a decisive influence on the magnitude of the NPV obtained during the simulation period. An increase on the NPV was observed under the HAD A1B and HIR A1B scenarios for all countries, compared to CCLM A1B and CCLM B1 scenarios. Moreover,

the relative loss in NPV for increasing deadwood biomass on forest stands reduced under the HAD A1B and HIR A1B trajectories, due to the increased growth rates and deadwood input under these scenarios.

Robust solutions

The outcomes for robust management regimes are represented as dashed lines in Fig. 2. Taking into account that a same management is selected under the robust approach, regardless of the climate change scenario, a loss in NPV is observed in consequence of not selecting the deterministic optimum. For the majority of countries, the robust solution caused moderate NPV reductions, with Spain and Switzerland displaying the strongest sensitivity to the choice of robust management regimes. The impact of the robust solution was negligible when no deadwood maintenance requirements were enforced and when the maximum deadwood production was required. The regret of the first and last solution is approximately zero (Fig. 2), indicating a cheap implementation of robust managements when the only objective is the NPV maximization or deadwood maximization. Conversely, the regret increased with an increased requirement for deadwood biomass, especially for mid-range values (between 20 and 80%) of the maximum deadwood production.

The regret caused by the robust solutions varied under different climate change scenarios. The loss in NPV was higher for the climate change scenario HAD A1B. This indicates a divergence between the robust management strategy and the deterministic optimum management strategy for HAD A1B, whereas for the remaining scenarios the deterministic and robust solutions were similar. Overall, the CCLM B1 scenario displayed the lowest regret, indicating the optimum managements for this climate change scenario were similar to the robust solutions.

Cost of deadwood and optimal management regimes

Given that the maintenance of deadwood in forest stands requires a reduction in management intensity, there is an opportunity cost for forest owners adopting biodiversity-oriented management regimes. Figure 3 shows the opportunity cost, in terms of foregone harvesting revenues, for achieving the highest deadwood maintenance. The cost ranged between 50.3 and 332.2 €/t DW with an average value of 131.7 €/t DW. Similar to the trade-off displayed in Fig. 2, countries in Central Europe with high wood prices, namely Austria, Switzerland and France, showed the highest opportunity cost, while eastern European countries showed the cheapest maintenance of deadwood in their forest stands. In addition, the increased growth rates and profitability under the HAD A1B climate scenario led to an increased opportunity cost
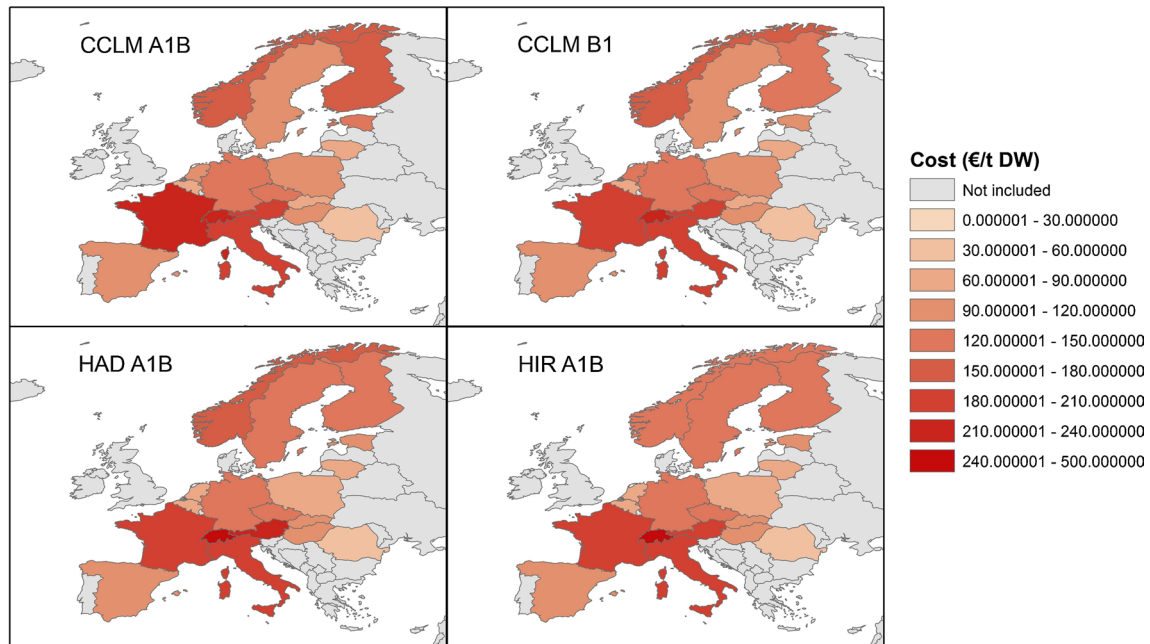
Fig. 3 The figure shows the cost of deadwood biomass production for each country included in our study, for the maximum deadwood production and for each climate change scenario considered

for maintaining deadwood on stands, 5% higher than the CCLM B1 and 2% higher than the CCLM A1B trajectory. However, taking into account the higher profitability under this trajectory, the relative loss in terms of the percentage of foregone NPV was lower compared to the CCLM A1B and B1 trajectories.

The frequency of management alternatives selected as optimal and robust solution is shown in Fig. 4. The optimum management solutions (Fig. 4a) dominantly displayed management regimes with at least two increased thinning intensity interventions. The most frequent management regimes were management 57 (M57-III), with increased thinning intensity in all decision points, management 49 (M57-IIU), with increased thinning intensity in the first two decision points and BAU thinning until the end of the simulation, and management 1 (M01-NNN) with no thinning interventions. The first two management regimes were selected for low levels of deadwood maintenance (low fdead value), whereas management 1 was the most frequent for high deadwood requirements. Intermediate deadwood requirements led to a strong diversification of the management regimes in each country and species. In general, for fdead values above 0.8, the management regimes with no thinning after year 30 were selected, whereas for fdead values below 0.2 increased thinning intensity was dominant.

We perceived that the share of no thinning interventions increased for large fdead values, compared to the individual optimum managements. Managements 1 (M1-NNN) and 7 (M07-NDN) were the most frequent for maintaining higher amounts of deadwood. As management regimes may differ in the production of deadwood in different climatic conditions, it was necessary to decrease thinning intensity for maintaining the deadwood production levels stable. Thus, for guaranteeing this long-term deadwood maintenance, regardless of the climate change scenario, regimes with no intervention or low intensity interventions were demanded.

We assumed in our study a z value equal to 0.5 in the robust optimization model, balancing optimality and robustness. Therefore, one open question is how the optimal solution responds to modifications in this parameter. Figure 5 shows the average NPV across all countries of the robust solution in each climate change scenario. Our results show that the optimal solution is relatively stable for a z value above 0.2. When $z < 0.2$, more conservative solutions were selected and forest profitability reduced on average by 1000 €/ha.

Discussion

Deadwood maintenance

We perceived variable responses of deadwood production in different regions. In boreal forests, due to temperature limitations and short length of the growing season, forests grow at lower rates (Lindner et al. 2010). Thus, competition between trees starts later in the stand rotation, compared to temperate ecosystems, and deadwood input in these areas is reduced,
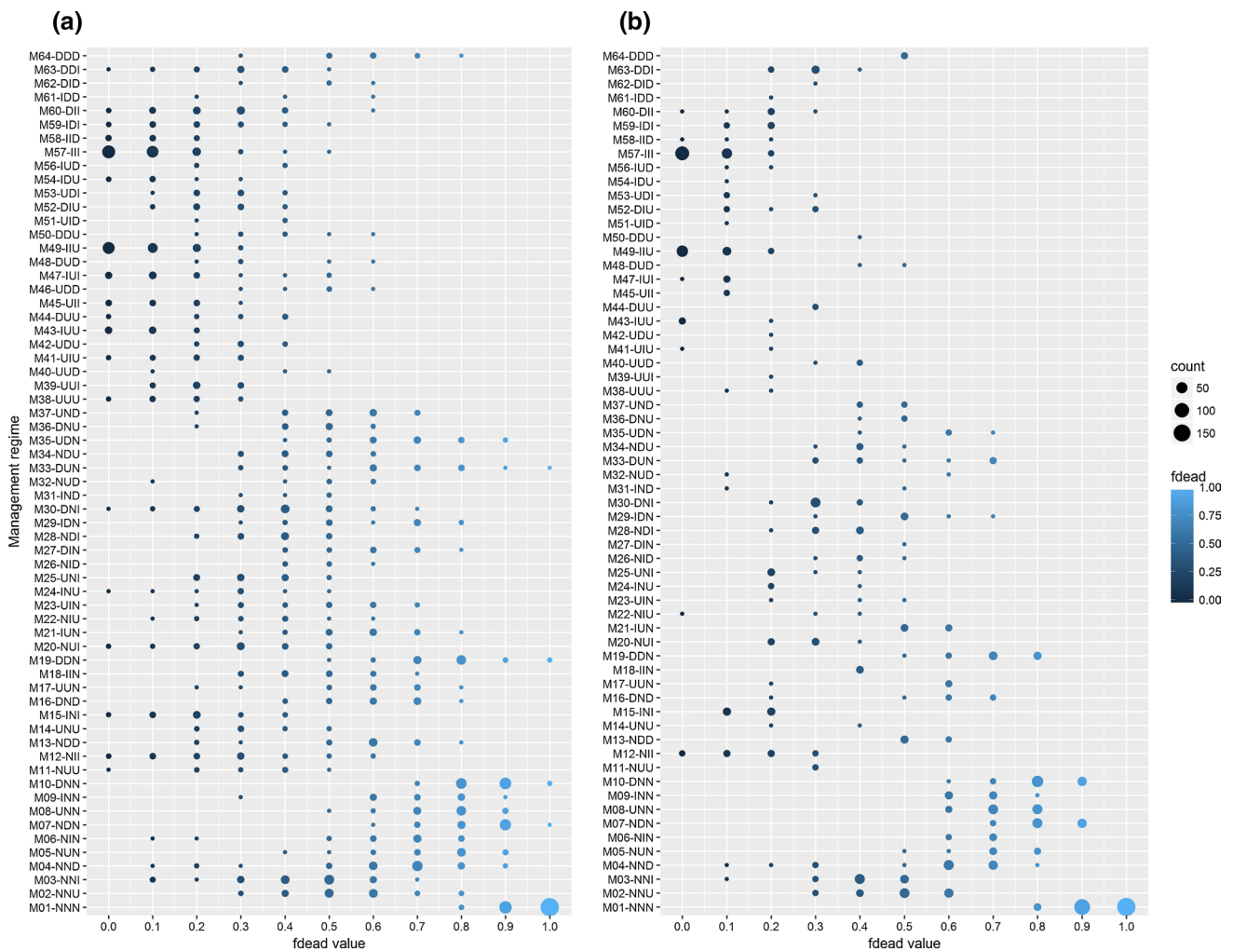
(a)

(b)

Fig. 4 Frequency of thinning regimes. The figure shows the relative frequency of the choice of each management regime for deterministic (**a**) and robust (**b**) solutions. The color gradient represents the values assigned for the fdead parameter in the optimization, i.e., the amount of deadwood requirement in relation to the maximum for each coun-try and species. The optimal management is described by its number and a three-character sequence, indicating the thinning intensity at each decision point (U = BAU, I = increased, D = decreased, N = no thinning)
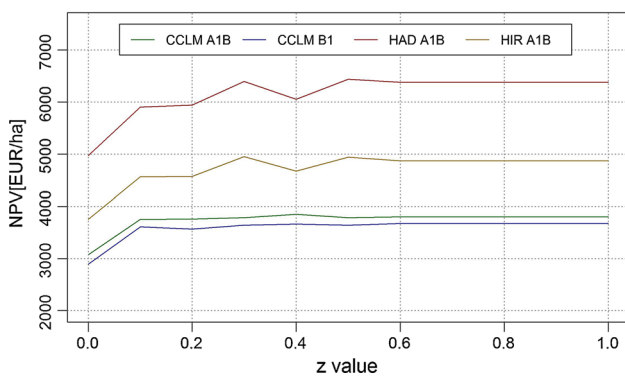

Fig. 5 Sensitivity of the robust solution to the z value for each climate change scenario. Low z values represent a focus on the worst case, whereas high z values increase the weight of the best case in the objective function

even for management regimes with no thinning intervention. Moreover, we observed a strong influence of the climate scenario on deadwood biomass. Deadwood biomass was higher under HAD A1B scenario, notably for Scandinavian countries. As growth rates increased due to carbon fertilization and higher temperatures in boreal temperature-limited forests, the stand stock increased more rapidly, leading to an earlier competition and increasing deadwood input. Mazziotta et al. (2014) found similar results analyzing the impacts of management and climate change on deadwood amounts in a boreal forest. Similarly, considering the dependence on decay rates to temperature and precipitation, climate change is expected to alter deadwood dynamics. Mazziotta et al. (2014) and Russell et al. (2014) found increasing decay rates due to the predicted increase in temperatures. Precipitation and water content are also determinant to deadwood decay

rates. Therefore, the increased deadwood input and lower precipitation due to climate change may have contributed to the faster deadwood accumulation in our analysis.

We show that increasing deadwood amounts require a reduction management intensity. This might prove a difficult challenge in the future. The demand for renewable energy resources for mitigating climate change may increase, for example through the use of biomass energy in substitution to fossil fuels (Creutzig et al. 2014; Lamers and Junginger 2013; Repo et al. 2012). As pointed by Verkerk et al. (2011), increasing biomass removals might reduce deadwood availability and jeopardize the habitat for saproxylic species in Europe.

Economic implications

Our results indicated that significant improvements in deadwood availability could be achieved with moderate economic losses up to 20% of the maximum deadwood biomass (within the range of a precautionary threshold of 20 m^3/ha), thus benefiting saproxylic organisms and enhancing forest biodiversity. Higher thresholds for deadwood maintenance would result in a stronger NPV reduction, as less intensive management regimes would be required, reducing harvesting revenues. This cost is enhanced in areas with simultaneously high wood prices and low growth rates, for example in oak forests, as the low deadwood input combined with higher profitability of forest management (due to high capitalization rates of the stands) requires a strong reduction in management intensity. Our results corroborate with similar studies, aiming at balancing forest profitability and biodiversity (e.g., Mönkkönen et al. 2014; Xabadia et al. 2014; Yousefpour and Hanewinkel 2014), that report decreasing forest profitability applying management regimes aiming at biodiversity conservation, with NPV losses depending on stand structure and conservation practices.

The current deadwood volume in Europe amounts on average to 11.5 m^3/ha, ranging from 8 m^3/ha in Scandinavian to 20 m^3/ha in Central Europe (MCPFE 2015). This is well below the thresholds recommended in the literature, typically ranging from 20 to 50 m^3/ha (Müller and Bütler 2010). This will require an additional deadwood accumulation ranging from 8.5 to 38.5 m^3/ha, thus implying the necessity to apply management regimes with reduced thinning intensity or artificial deadwood enrichment. Taking into account the costs calculated through the maximum deadwood biomass production, this may be achieved at a cost ranging from 390 to 1767 €/ha on average (1 t DW = 2.5 m^3).

We observed impacts of both species composition and biome on the costs for increasing deadwood volume. Countries with large contribution of *Fagus sylvatica* and Scandinavian countries had lower costs than Central European countries. These were related to the lower forest profitability in these areas, due to reduced growth rates and wood prices, leading to a lower opportunity cost of deadwood production.

With the increase in deadwood thresholds, the trade-off between profitability and deadwood maintenance was enhanced, requiring no management interventions for long time periods, in order to maintain deadwood volume at desirable levels. The combination of thinning intensity with other management practices, such as leaving harvested logs, high stumps, or allowing for the maintenance of deadwood resulting from natural disturbance and species with low market value, might contribute to reducing the costs of increasing deadwood quantities (Lonsdale et al. 2008; Ranius and Kindvall 2004; Zhou and Gong 2004).

Robust solutions

NPV losses due to robustness were reasonable for the majority of countries and climate change scenarios. In this sense, RO tools provide a suitable basis for supporting forest management actions, allowing managers to exchange optimality for stable outcomes under climate uncertainty, with reasonable impacts on the NPV. Managers are therefore capable of selecting a safe course of action at the beginning of the planning horizon reducing vulnerability to large economic losses in the future.

Among the four climate change scenarios, we defined equal weights to average the minimum and maximum regrets, in terms of the NPV in our objective function. Nevertheless, managers might adjust the values of the weighted sum according to their preferences. Risk-averse forest managers might include only the worst case regret into the objective function, minimizing the worst regret related to climate change uncertainty. In this case, they would select a management regime with the best result, in case the least favorable climate change scenario becomes true, guaranteeing the performance of the worst case. However, as an alternative regime might exhibit slightly poorer results under the least favorable climate change scenario, while showing substantially superior performance on the remaining climate change scenarios, a foregone opportunity might occur. In this sense, worst case approaches have received criticism on the literature for yielding excessively conservative responses (Bertsimas and Thiele 2006; Fischetti and Monaci 2009). Conversely, risk-taking forest managers might assign higher value for the best regret, thus taking into account the possibility of a great benefit in case a favorable climate change scenario becomes true, however at a greater performance risk if the least favorable climate change scenario occurs.

The application of tailored management regimes to cope with climate change must consider that new information on climate change continues to become available, making it crucial to update uncertainties related climate change scenarios

and adjust the decision making process. Yousefpour et al. (2013) propose a framework for updating climate change beliefs for forest management implementation, adopting a Bayesian approach. In this sense, managers might start with robust management regimes and update the uncertainties related to each climate change scenario using Bayes' theorem, evaluating the more likely development paths and integrating this information in the robust optimization problem. Furthermore, a constant evaluation and updating of management actions are recommended, in order to compare expected with obtained forest outcomes, allowing the selection of the best management options and obtaining the highest possible benefits from forests under climate change.

Conclusions

Climate change poses a major challenge for the management of forest resources, as it requires that decision making is performed based on only partial information about future climatic development. In the face of this deep uncertainty, robust optimization techniques provide a solid basis for forest planning, allowing for safeguarding the provision of ecosystem goods and services under uncertainty. Moreover, taking into account the uncertain impacts of climate change on forests, with possible occurrence feedbacks, new interactions and disruption of ecosystems when thresholds are surpassed, biodiversity will play a major role in ensuring forest resilience and facilitating the recovery of ecosystem functioning. Here, we demonstrate how these problems can be tackled efficiently, through the application of a robust optimization model for simultaneous maximization of forest profitability and respecting the maintenance of deadwood volume above desirable levels. We conclude that integrating climate change uncertainty and biodiversity into forest planning is key for guaranteeing that the goals of forest managers are achieved in the future.

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