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Planning for bark beetle disturbance in production forests: A regional forest optimization case study in Norway

Kyle Eyvindson [a,b,*], Victor F. Strîmbu [b], Joyce Romeiro [c], Tron Eid [b], Annika Kangas [d]

[a] Department of Forest Sciences, University of Helsinki, P.O. Box 27, FI-00014 Helsinki, Finland
[b] Faculty of Environmental Sciences and Natural Resource Management, Norwegian University of Life Sciences (NMBU), Ås, Norway
[c] Division of Forest and Forest Resources, NIBIO (Norwegian Institute for Bioeconomy Research), Høgskoleveien 8, 1433 Ås, Norway
[d] Natural Resources Institute Finland (Luke), Bioeconomy and environment, Yliopistokatu 6, 80101 Joensuu, Finland

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ABSTRACT

Increasing disturbance pressure from the spruce bark beetle (*Ips typographus*) challenges the reliability of timber supply in managed boreal forests. This study evaluates alternative optimization approaches for integrating bark beetle damage into regional forest planning in southern Norway. Using a simulation and optimization process, we compare three alternative optimization approaches: (i) deterministic linear programming ignoring disturbance risk, (ii) robust optimization protecting even-flow constraints against income variability, and (iii) stochastic programming using probabilistic disturbance scenarios. Two planning objectives were examined: maximizing the net present value (NPV) alone, and maximizing NPV subject to a minimum periodic timber harvest requirement. When only NPV was maximized, differences among the solutions were minor. The stochastic solution yielded a slightly higher expected NPV (0.1%) through earlier harvesting. Approximately 22% of deterministic scenarios outperformed the stochastic solution, highlighting the limited economic gains when focused on a purely financial objective. When prioritizing a targeted periodic timber supply the deterministic solution resulted in systematic harvest shortfalls under realized disturbances while the robust solution reduced shortfalls by increasing periodic harvests. The stochastic formulation substantially improved supply reliability, reducing expected harvest shortfalls from 1.9% (deterministic) and 1.1% (robust) to nearly 0% for the stochastic solution, albeit with a moderate reduction in the expected NPV. Results demonstrate that the value of incorporating disturbance uncertainty depends on management objectives. While economic efficiency alone provides limited incentive for risk integration, maintaining stable timber supply under increasing disturbance pressure benefits substantially from stochastic planning approaches.

Introduction

Managed boreal forests are important sources of industrial roundwood, rural employment, and economic activity in northern Europe. In Norway, the forest sector contributes a minor component of the total Norwegian GDP (~0.1 – 0.2%), with value provided across a variety of ecosystem services (Helseth et al., 2024), with much of this depending on a predictable flow of raw material from production forests. Planning the use of forests contributes to both the economic value obtained by the forest owner, and act as a supply coordination function for industrial needs. Harvest planning should generate value for the forest owner, but also should support relatively stable timber deliveries to the industry (Simard et al., 2023).

Scandinavian forest planning has traditionally prioritized the application of economically efficient management, through an even-aged forest structure, while also accommodating other objectives (Schelhaas et al., 2018a; Siiskonen, 2013). This has resulted in the semi-natural, rather homogenized forest landscape with the most economically valuable tree species dominating the landscape. In the Nordic boreal region, Norway spruce (*Picea abies* (L.) Karst.) are favored on productive sites, whereas Scots pine (*Pinus sylvestris*) are favored on drier sites. The choice of species involve different disturbance risks. Scots pine regeneration can be impacted by moose browsing (Bergqvist et al., 2014), while spruce-dominated stands are vulnerable to the European spruce bark beetle (*Ips typographus*) (Romeiro et al., 2022). Once established, silvicultural actions are then taken to prioritize the growth

* Corresponding author.
E-mail address: kyle.eyvindson@helsinki.fi (K. Eyvindson).

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of these tree species in the forest stand. When the threat of biotic and abiotic disturbances is low, this strategy of management has shown that it can produce large quantities of biomass for the industry. However, there is an expectation that with climate change both biotic and abiotic disturbances will increase (Patacca et al., 2023). This change in disturbance patterns can necessitate a shift in forest management strategy to prioritize prevention of excessive losses over enhanced biomass production.

Ips typographus is endemic in boreal and temperate spruce forests, with its primary habitat being damaged spruce trees. Healthy spruce trees are normally able to fend off the beetle (Jakuš et al., 2011), however when bark beetle is in an epidemic state, the defenses of a healthy tree can be overwhelmed by swarms of beetles (Hlásny et al., 2019). In Norway, projected bark beetle damage has been estimated at between 1.7 to 11.3 m^3/ha in 9% of Norway's productive forest regions (Romeiro et al., 2024). The area of highest concern is the spruce-dominated areas of southern and southeastern Norway. Proactive management to limit the extent of bark beetle damage is difficult, as damaged trees need to be detected, before the bark beetles attack additional trees. However, detecting them is difficult until the tree has died. There is some promise of early detection of bark beetle damaged trees through the use of multi-spectral scanning (Honkavaara et al., 2020), or through the use of trained dogs (Kangaslampi and Tikkanen, 2026; Vošvrdová et al., 2023) or sensors to replicate dogs nose (Hüttnerová and Surový, 2024) to detect the presence of bark beetles. However, monitoring the bark beetles over large areas requires regular assessment and is likely cost-prohibitive, unless the search can be focused on most vulnerable areas.

In recent history, there have only been small bark beetle outbreaks across Scandinavia, often linked to storm damage (Annila, 1978). The frequency and intensity of bark beetle outbreaks in central Europe have been increasing, with dramatic damage occurring to large regions of forests. Recent climatic events in southern Scandinavia has highlighted the susceptibility of the region to biotic and abiotic damage (Buras et al., 2020). Increased temperature and changing precipitation patterns can lead to regions that are highly susceptible to biotic damage (Marini et al., 2017; Müller et al., 2022; Romeiro et al., 2022), with distressed trees having weakened defenses towards the bark beetle (Netherer et al., 2015).

Forest planning literature has long recognized that disturbance risk can be mitigated by conducting harvest earlier under some risk settings (Bastit et al., 2023). Similar arguments have been made for increasing disturbance pressure in European forests (Zimová et al., 2020), and recent stand-level work for Norway showed that incorporating bark beetle risk can shorten NPV-maximizing rotations and alter species choices (Romeiro et al., 2025). These studies clarify how disturbance risk affects stand-level economic decisions. However, it remains unclear whether different representations of uncertainty produce different regional planning outcomes when the objective extends beyond expected NPV to include other objectives, for instance the reliability of periodic timber supply.

This distinction is important because short- and medium-term supply reliability cannot be solved only through long-term silvicultural adaptation. Increasing tree species diversity or changing stand structure may reduce future vulnerability, but such changes unfold over several decades in Norwegian production forests. In the near term, planners must work with the existing age-class and species structure, including past decisions that created spruce-dominated landscapes in parts of southern Scandinavia (Schelhaas et al., 2018b). Regional harvest scheduling under disturbance uncertainty is therefore a practical planning problem: the same disturbance that has modest effects on expected NPV may still create periods in which realized harvest volumes fall below supply commitments.

To better understand the impacts and effects of bark beetle disturbances for timber production and forest planning, we examine regional planning case in southeastern Norway that integrates bark beetle damage. Forest growth and development are simulated using a forest simulator extended with a bark beetle damage probability model. We tested three alternative approaches for managing the risk of disturbances. The first model is deterministic and ignores the possibility of bark beetle damage. The second model uses a robust optimization formulation that adds a protection function to the timber supply constraint. The third model uses stochastic programming to incorporate a large set of possible bark beetle damage scenarios. These scenarios represent uncertainty in both the timings and damage intensity of potential attacks.

The objectives of this study are to evaluate approaches of incorporating bark beetle damage uncertainty into planning approaches and to assess the importance of including this uncertainty into the planning approach. This is accomplished by evaluating two commonly applied forest planning approaches (maximizing NPV, maximizing the even-flow of timber resources) across three different methods to construct forest management plans.

Material and methods

Materials

The case study was focused on several municipalities in Vestfold and Telemark counties, located in southeastern Norway (Fig. 1). These municipalities (Horten, Holmestrand, Tønsberg, Sandefjord, Larvik, Porsgrunn, Skien, Færder, and Siljan) collectively cover 2107 km^2, with approximately 91,926 ha of productive forest. This region was selected as it includes spruce-dominated production forests and experienced major bark beetle outbreaks during the late 1970s (NIBIO, 2023). Data from 102 plots from the Norwegian National Forest Inventory was used in this study. The data is collected using a circular plot size of 250 m^2 on a 3 × 3 km grid (Breidenbach et al., 2020).

Simulations

Plot level forest development was simulated with GAYA 2.0, a forest simulator adapted to Norwegian conditions and previously extended to include stochastic disturbances such as bark beetle and snow break damage (Romeiro et al., 2025; Strîmbu et al., 2023, 2025). GAYA 2.0 uses a branching approach to generate alternative treatment schedules for each plot (Siitonen, 1993). To adapt this approach for stochastic programming, we first constructed a set of possible schedules for each forest plot, and then simulated their outcomes under alternative disturbance realizations. This enabled the choice of treatment to be consistent across the simulations. Each plot had an average of 100 alternative treatment schedules simulated (median 88; standard deviation 62.5).

To reflect near term forest planning conditions, we have opted to simulate the development of the forest for a total of 60 years. This has been constructed as twelve 5-year periods. Silvicultural actions were assumed to occur at the start of each 5-year period. This convention means that bark beetle exposure within a period was evaluated after the scheduled treatment for the period has been applied. To construct a probabilistically realistic set of bark beetle damages across the entire set of forest plots, we re-ran the simulations incorporating the bark beetle model a total of 100 times, and one additional time with the assumption of no occurrence of bark beetle attacks.

Economic outcomes were evaluated using the latest estimates of economic parameters (Landbruksdirektoratet, 2025). We assumed that the price of timber was 625, 575 and 400 NOK per m^3 for spruce, pine and birch logs, 275, 250 and 300 NOK per m^3 for spruce, pine and birch pulp. Felling and forwarding costs were based on machine-hour costs of 1500 and 1250 NOK. Silvicultural costs were estimated at 8 (12) NOK per spruce and pine (birch) sapling to plant, 4500 NOK/ha for scarification, and 2000 NOK/ha to conduct tending. Conversion from NOK to EUR is 0.0853 on average during 2025. Future costs and profits were

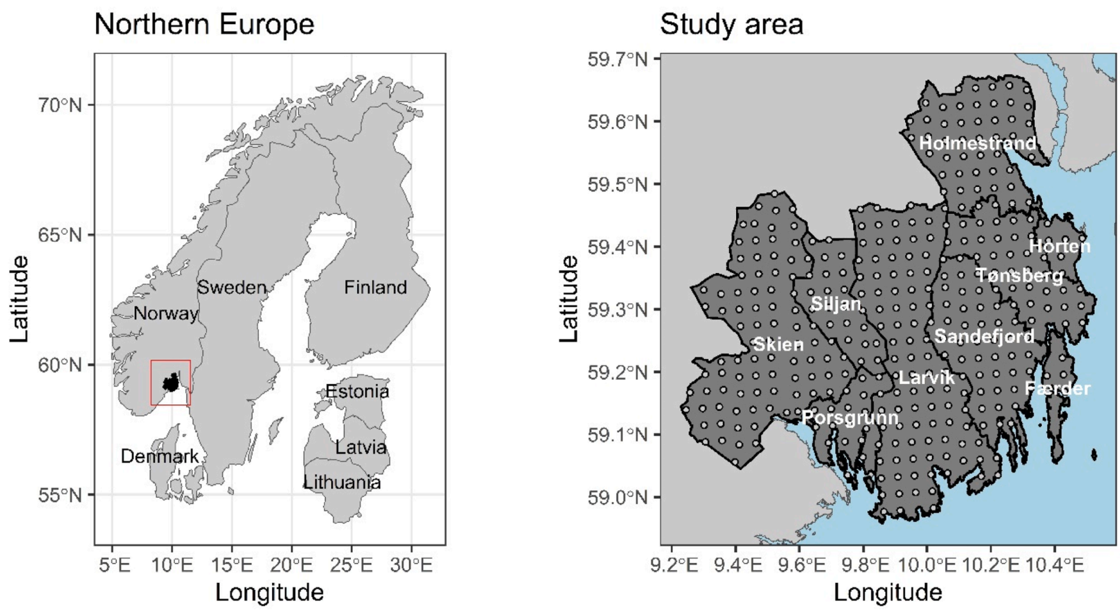

Fig. 1. Study area: nine municipalities in southern Norway. On the right, circles denote the Norwegian NFI plot locations. Only plots classified as productive forest land are included in the analysis.

discounted using a 3% rate.

The bark beetle models

Bark beetle damage was simulated using the model proposed by Seidl et al. (Seidl et al., 2008). This model has been assessed for its use in Norwegian conditions (Romeiro et al., 2024), producing reasonable results. The model predicts annual bark beetle damage probability (pBB) and damage intensity (iBB) based on the stand characteristics and the climatic conditions. Damage intensity represents the proportion of wood volume lost due to the attack. The model was integrated in GAYA 2.0 by increasing the natural mortality of the plot, depending on the probability and intensity of the bark beetle attack.

To generate a large number of simulations outcomes we used a Monte Carlo approach. For each plot and each feasible schedule for that plot we generated a set of 100 bark beetle disturbance scenarios. Each scenario consists of bark beetle attack realizations throughout the periods of the schedule. Since GAYA 2.0 operates over periods of several years (e.g., for this study n = 5 years), the probability and intensity of bark beetle attacks were compounded at the period level based on the number of years with attack (k) out of the total number of years in the period (n), and assuming that pBB is equal and independent for all years in the period:

$$pBB(k,n) = \binom{n}{k} pBB^k (1 - pBB)^{n-k}$$

$$iBB(k,n) = 1 - (1 - iBB)^k$$

For a given schedule, bark beetle attack scenarios were simulated by traversing the schedule from the first to the last period. For each period, the number of attack years, k, was randomly drawn from the probability distribution $pBB(k, n)$. The corresponding cumulative mortality rate, $iBB(k,n)$, was then calculated and applied by removing the appropriate number of trees. Forest development was subsequently simulated using the remaining trees as the starting condition for the next period.

To appropriately evaluate the optimized solutions, we generated a separate set of 100 scenarios to evaluate the solution quality. This separation avoids rewarding a solution simply because it was optimized for a particular set of scenarios.

The specific number of scenarios generated depends on how representative the set of scenarios is, which depend on the problem to be solved and source of uncertainty (Eyvindson and Kangas, 2016). To avoid re-sampling and re-construction of scenario sets, we used the earlier study as a guide to identify an appropriate size of the scenario set. This assumption will be reflected on in the discussion, justifying why this particular scenario size is reasonable for this problem.

Optimization formulations

All formulations follow the Model I forest planning structure (Johnson and Scheurman, 1977). In this implementation, the decision variable x_{jk} is a non-negative value indicating the proportion of plot j is applied to alternative management option k. All formulations apply the same decision variables and alternative management options, however they differ in how they represent bark beetle uncertainty and how they enforce the periodic timber-supply target (Table 1). This distinction is important when interpreting the results. Each formulation suggests an alternative solution that is optimal for how disturbances are incorporated in the model, however alternative formulations incorporate the uncertainty in different ways.

Two planning cases were considered. In the first case, the model maximized NPV without imposing a periodic timber supply target. In the

Table 1
Summary of how the deterministic, robust, and stochastic formulations represent bark beetle uncertainty, timber-supply targets, and the role of NPV.

Formulation	Representation of bark beetle uncertainty	Timber-supply target	Role of NPV
Deterministic	No future bark beetle damage is represented during optimization	Hard periodic target under the no-damage projection	Objective in both planning cases
Robust	A safety margin is added to the periodic target using an uncertainty interval	Protected hard target	Objective in both planning cases
Stochastic	Multiple bark beetle scenarios are represented explicitly	Scenario-based downside shortfall, measured with CVaR	Main objective in the NPV-only case; efficiency measure in the reliability case

second case, the model prioritized a minimum periodic harvest target, denoted as b_t. In the implementation used, we set b_t to 5.9 m^3 per ha per year of timber produced per year. For the deterministic and robust optimization, this target was imposed as a hard constraint. For the stochastic optimization, a hard target in every scenario would force the solution prioritize the extreme worst case scenario. To relax this assumption we represented the same planning concern as a downside shortfall measure, evaluated as the Conditional Value at Risk (CVaR). In this formulation, the NPV is included as an efficiency value, to ensure we obtain the required timber at the best possible value.

Deterministic optimization

The deterministic model represents the case in which future bark beetle damage is ignored during the optimization. The formulation is structured to prioritize the acquisition of the periodic income as a required constraint and then to maximize NPV. This model requires a single simulation of the forest to be performed; in this case we assume that no damage or uncertainty will occur. This approach takes a rather optimistic perspective on the development of forest resources. The deterministic optimization approach is to:

$$\max NPV \tag{1}$$

Subject to:

$$NPV = \sum_{t\in T}\frac{\bar{I}_t}{(1+r)^{(ts-u)}} + \sum_{j\in J}\sum_{k\in K_j}\frac{PV_{jk}x_{jk}}{(1+r)^{(s\#T)}} \tag{2}$$

$$\bar{I}_t = \sum_{j\in J}\sum_{k\in K_j}\sum_{a\in A}P^a\overline{H}_{ajkt}x_{jk} - \sum_{j\in J}\sum_{k\in K_j}P^cC_{jkt}x_{jk}, \forall\, t\in T \tag{3}$$

$$\bar{I}_t \geq b_t,\ \forall\, t\in T \tag{4}$$

$$\sum_{k\in K_j}x_{jk} = 1, \forall\, j\in J \tag{5}$$

where the variables are used for all formulations are defined in Table 2. The objective function is presented in Eq. (1) maximizes the NPV. The NPV is evaluated in Eq. (2), where the discounted periodic flow of incomes are summed together with the remaining value at the end of the planning horizon. The remaining value of the forest is calculated using a fixed schedule, based on the plots site index, dominant species and discount rate, with the approach described in Strîmbu et al. (2023). The periodic incomes are evaluated in Eq. (3), where the timber assortments are multiplied by the price subtracting the costs of silvicultural activities. Eq. (4) presents the constraint requiring that all periodic incomes exceed a predefined target. Eq. (5) is an area constraint, requiring that each forest plot undergo some form of management. The bar above the variable indicates that a single average value is used to represent the variable.

Robust optimization

The robust optimization model extends the deterministic model by incorporating uncertainty into the even flow income requirement. This model follows the deterministic optimization model, seeking to ensure an even flow of income across all time horizons and then maximizes NPV. The key difference is that the robust optimization formulation protects the even flow of income from nominal deviations.

Following Palma & Nelson (2009), each uncertain income coefficient is assumed to vary within a symmetric interval around the expected value. In this notation, $\overline{H}_{ajkt}$ is the expected estimate of harvest, while ΔH_{ajkt} is the maximum possible deviation from that estimate. This variable should be interpreted as a deviation bound, rather than as a point estimate. The specific values of ΔH_{ajkt} should reflect the best available information on what the interval of possible values may be. In this case, we estimated ΔH_{ajkt} to be 2.5% of the stand volume

Table 2
Notation used in the stochastic programming models:.

Symbol	Model (All = A, Stochastic = S, Robust = R, Deterministic = D	Description
Sets		
A	A	Timber assortments
J	A	The set of plots representing the forest holding
J_t^D	R	The set of uncertain coefficients for the even-flow constraint
K_j	A	Management prescriptions for plot j
N	S	The set of scenarios representing the forest holding level bark beetle uncertainty
T	A	The set of time periods under consideration
Variables		
$CVaR_*$	S	The maximum conditional value at risk from all periods evaluated using a confidence level of α
$CVaR_t$	S	The conditional value at risk for period t
$\mathbb{E}(NPV)$	S	The expected net present value for the set of scenarios
I_{nt}	S	The income generated during scenario n and period t
$\bar{I}_t$	D, R	The income generated during period t
L_{nt}	S	The income generated during scenario n and period t
NPV_n	S	The net present value of a scenario n
NPV	D, R	The net present value
PV_{jkn}	S	The remaining productive value from plot j and management schedule k for scenario n
PV_{jk}	D, R	The remaining productive value from plot j and management schedule k
u_t	R	robust optimization variables
w_{jkt}	R	robust optimization variables
x_{jk}	A	The decision variable for plot j and management schedule k
Z_t	S	The value at risk for period t
Parameters		
α	S	CvaR confidence interval
b_t	A	The income target for each period t
C_{jknt}	S	The silvicultural actions for plot j, management schedule k, scenario n, and period t
C_{jkt}	D, R	The silvicultural actions for plot j, management schedule k and period t
Γ_t^D	R	The parameter to control the level of protection for time t.
H_{ajknt}	S	The harvest volume for assortment a, plot j, management schedule k, scenario n, and period t
$\overline{H}_{ajkt}$	D, R	The expected harvest volume for assortment a, plot j, management schedule k, and period t
ΔH_{ajkt}	R	The uncertainty interval component around the harvest volume for assortment a, plot j, management schedule k, and period t
p_n	S	The probability of a scenario n
P^a, P^c	A	The value of the assortment of timber (a), and the costs of silvicultural activities (c)
r	A	A parameter describing the discount rate applied
ρ	S	A small positive value to act as an augmentation term

The total income deviations in period, $\widehat{I}_t$, is calculated from the deviations in the harvest for the selected management activities. In this way, $\widehat{I}_t$ is the aggregate potential income deviations implied from the uncertain coefficients ΔH_{ajkt} and the decision variable x_{jk}.

The degree of protection against these deviations is controlled by the parameter Γ. This parameter is selected by the decision maker and determines how much of the potential income deviation must be protected against in each period. When $\Gamma = 0$, the robust formulation reduces to the deterministic optimization problem. As Γ increases, the model becomes more conservative by protecting against larger negative deviations in income, which will reduce the NPV while stabilizing the income flows.

The robust optimization problem is formulated as:

$$\max NPV \tag{6}$$

Subject to:

$$NPV = \sum_{t\in T}\frac{\bar{I}_t}{(1+r)^{(ts-u)}} + \sum_{j\in J}\sum_{k\in K_j}\frac{PV_{jk}x_{jk}}{(1+r)^{(s\#T)}} \tag{7}$$

$$\bar{I}_t = \sum_{j\in J}\sum_{k\in K_j}\sum_{a\in A}P^a\bar{H}_{ajkt}x_{jk} - \sum_{j\in J}\sum_{k\in K_j}P^cC_{jkt}x_{jk}, \forall\ t\in T \tag{8}$$

$$\widehat{I}_t = \sum_{j\in J}\sum_{k\in K_j}\sum_{a\in A}P^a\Delta H_{ajkt}x_{jk}, \forall\ t\in T \tag{9}$$

$$\bar{I}_t - \Gamma_t^D u_t - \sum_{(j,k)\in J_t^D} w_{jkt} \geq b_t,\ \ \forall\ t\in T \tag{10}$$

$$u_t + w_{jkt} \geq \widehat{I}_t,\ \ \forall (j,k)\in J_t^D,\ \ t\in T \tag{11}$$

$$u_t \geq 0,\ \ \forall\ t\in T \tag{12}$$

$$w_{jkt} \geq 0,\ \ \forall (j,k)\in J_t^D,\ \ t\in T \tag{13}$$

$$\sum_{k\in K_j} x_{jk} = 1, \forall\ j\in J \tag{14}$$

In addition to the common equations with the deterministic optimization model, to enable the robust optimization functions we add Eqs. (7)–14. Eq. (9) quantifies the magnitude of potential income deviation due to uncertainty at each time period. Eq. (10) acts as a periodic income flow constraint, introducing a protection function which increases the income harvest requirement. Eq. (11) ensures that the variance is covered by both components in how the uncertainty is managed (either u or w), Eqs. (12) and (13) are positivity requirements.

Stochastic optimization

The use of stochastic optimization requires uncertainty to be represented through a finite distribution of scenarios. Each scenario has the same candidate prescriptions, but different realizations of bark beetle damage, harvest volume, and NPV outcomes. The application of stochastic optimization requires the use of very few binding constraints, as a binding constraint will lead to solving for the worst-case solution. To address this concern, we replace the hard periodic target with a downside shortfall measure. For each period and scenario, the shortfall is the positive difference between the target (b_t) and the realized harvest volume. Shortfall is zero when the target is met or exceeded.

In this case, we used the Conditional Value at Risk (CVaR) as the downfall shortfall measure. We used CVaR as it represents the average value of the downside risk exceeding a specific percentage (α), and can be solved with linear programming (Rockafellar and Uryasev, 2000). This shift additionally requires that the CvaR and the net present value maximization are included in the objective function. To reflect the comparative importance of the objectives (constraints are prioritized over objectives), we reduce the importance of the expected NPV through the use of an augmentation value (ρ). The augmentation value is very small positive value to ensure the solution is efficient for NPV, and acts in a similar fashion as lexicographic optimization functions. As earlier mentioned, we use a set of 100 iterations (or scenarios) to represent the variation, which earlier research has shown is a sufficient number of scenarios to reflect uncertainty in this kind of decision framework (Eyvindson and Kangas, 2016).

The stochastic optimization problem is formulated as:

$$\min CVaR_* - \rho\mathbb{E}(NPV) \tag{15}$$

Subject to:

$$NPV_n = \sum_{t\in T}\frac{I_{nt}}{(1+r)^{(ts-u)}} + \sum_{j\in J}\sum_{k\in K_j}\frac{PV_{jkn}x_{jk}}{(1+r)^{(s\#T)}}, \forall\ n\in N \tag{16}$$

$$\mathbb{E}(NPV) = \sum_{n\in N} p_n NPV_n \tag{17}$$

$$CVaR_* \geq CVaR_t,\ \ \forall\ t\in T \tag{18}$$

$$I_{nt} = \sum_{j\in J}\sum_{k\in K_j}\sum_{a\in A}P^aH_{ajknt}x_{jk} - \sum_{j\in J}\sum_{k\in K_j}P^cC_{jknt}x_{jk}, \forall\ n\in N,\ \ t\in T \tag{19}$$

$$L_{nt} = [b_t - I_{nt}]^+\ \forall\ n\in N, t\in T \tag{20}$$

$$CVaR_t = Z_t + \frac{1}{(1-\alpha)N}\sum_{n\in N}[L_{nt} - Z_t]^+\ \forall\ t\in T \tag{21}$$

$$\sum_{k\in K_j} x_{jk} = 1, \forall\ j\in J \tag{22}$$

where the variables are defined in Table 1. All equations for this model are new, except for the decision variable requirement (Eq. (22)). This problem structure uses the same decision variable, allowing for a comparison of the sets of plot level decisions selected by the optimization approaches. The objective function (Eq. (15)) for this model aims to minimize the maximum conditional value at risk for all periods and then maximizes the NPV. To evaluate the NPV for each scenario, we apply Eq. (16), which applies Eq. (2) across all scenarios. The expected NPV is calculated based using Eq. (17), which is a summation of the probability of each scenario with that specific scenarios NPV. Eq. (18) requires that $CVaR_*$is greater than or equal to the periodic CvaR ($CVaR_t$). Eq. (19) is the stochastic representation of Eq. (3), evaluating the periodic income across each scenario and each time period. Eq. (20) evaluates the periodic losses for each scenario as the difference between the targeted minimum periodic income and the realized income. The superscript $+$ requires that only positive values are kept, otherwise the value is set to 0. Eq. (21) calculates the periodic CvaR.

Analyses

To enable a comparison of the solutions, we apply a unique set of bark beetle damage scenarios to each solution. The differences highlight how each optimization model incorporates risk, and the ability to mitigate that risk. This is possible as the set of decisions represent rather simple forest management actions and are the same across all modelling frameworks. The analysis differs depending on whether the model maximizes only NPV or includes periodic income requirements. In the single objective case, decisions are driven by NPV. Introducing periodic income constraints imposes additional timing requirements on harvest decisions. Additional analyses were conducted to explore how these alternative formulations influence harvest timing decisions.

Results

Maximizing NPV

When the objective function focuses on maximizing the NPV, the resulting management solutions differ only marginally across all formulations. The deterministic and robust formulations produce identical solutions. This reflects how the uncertainty is treated, as only the periodic income requirements are impacted by the uncertainty in those formulations. The stochastic solution produces a slightly higher expected NPV with an increase of 3.3 M NOK, or 0.08% across the region. However, a higher expected value does not imply that the stochastic solution is better than the deterministic solution in all realized outcomes.

This is illustrated through the distribution functions of NPV across scenarios (Fig. 2a). Although the stochastic solution dominates with respect to the expectation value, scenario-specific realizations show that realized uncertainty can produce cases where the deterministic solution is better than the stochastic solution. By comparing the scenario-wise solutions (Fig. 2b) approximately 22% of the cases result in the deterministic scenario having a better outcome than the stochastic case, although only a few scenarios exceed a 5 M NOK loss (0.12% loss) when compared to the deterministic solution.

The small NPV gain from the stochastic solution can be attributed to the changes in timings of the final fellings. Relative to the deterministic and robust solutions, the stochastic solution allocates approximately 2706 ha more forest area to final felling in the first period and shifts some final fellings one period earlier, while a smaller area was shifted one period later (Fig. 3). Interestingly, all other periods recommend harvests of the same size. This indicates a slight shift in the timing of the final felling, resulting in a minor increase in the total expected NPV. Due to the sampling design and optimization approach, the shift of the harvest requirements are always multiples of 902, as this is the representation of each plot area in this region of the Norwegian national forest inventory.

Prioritizing periodic income from timber harvested

When the planning problem priorities obtaining periodic income from timber, NPV no longer serves as the sole the objective. For both the deterministic and robust solution, the target for periodic income was imposed as a hard constraint and NPV was maximized among those solutions that met this hard constraint. In the stochastic problem formulation, the periodic income target was represented by downside shortfall (measured as CVaR) with the NPV retained as an efficiency term.

A trade-off exists between ensuring a periodic timber supply and maximizing the expected NPV. Relative to the deterministic solution, the stochastic solution reduces the expected NPV by almost 23 M NOK (0.6%), while the robust solution (using $\Gamma = 3.5$) reduces the expected NPV by almost 15 M NOK (0.4%, Fig. 4). These differences can be interpreted as the cost to improve the reliability of the periodic timber supply. Improving the certainty of the even-flow requirements is not free, and how this is addressed needs to be considered by the forest industry.

The main difference between these problem formulations is in how the periodic even-flow performs across the planning horizon. Both the robust and stochastic solutions perform better than the deterministic solution, as both delay some harvest to enable more certainty to periodic timber harvests. The core difference between the robust and stochastic formulation lies in how information about forest dynamics and damage risk is incorporated. By explicitly integrating scenarios of projected damage into the simulation, biophysical characteristics of the forest inform the simulation, and when represented by enough scenarios, enable the information to be used in the optimization. As the characteristics of the forest develop, the vulnerability of bark beetle damage shifts, and this can be addressed in stochastic optimization, and not in robust optimization. In a comprehensive exploration, we explore how the performance of the protection function changes with increasing

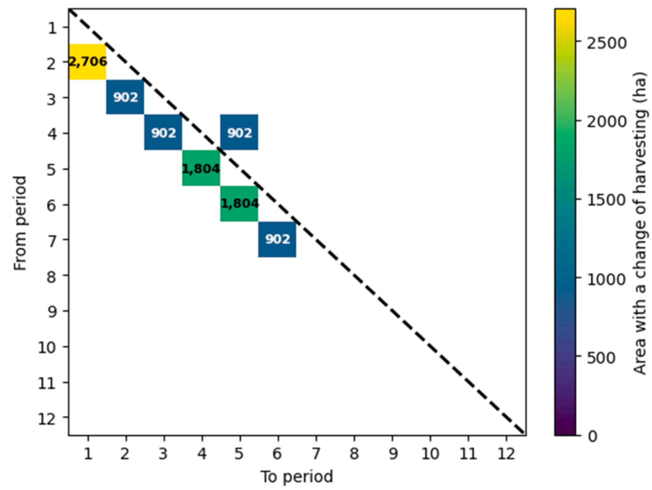

Fig. 3. Changes in final-felling timing in the NPV-only case when comparing the stochastic solution to the deterministic and robust solutions. Each cell shows the expanded forest area allocated to management alternatives whose final-felling period changed from the period on the horizontal axis to the period on the vertical axis. Cells below the diagonal line indicate earlier fellings; cells above the diagonal line indicate delayed final felling.

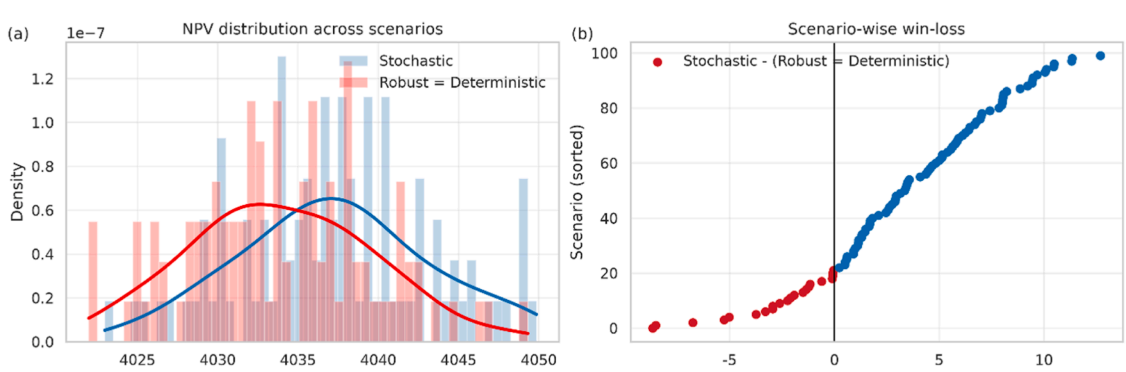

Fig. 2. (a) Distribution of net present value (NPV; M NOK) across scenarios for the stochastic solution and the deterministic/robust solution. Histograms and kernel density curves illustrate differences in central tendency and dispersion between the approaches. (b) Scenario-wise NPV differences (M NOK) between the stochastic and deterministic/robust solutions, sorted by magnitude.

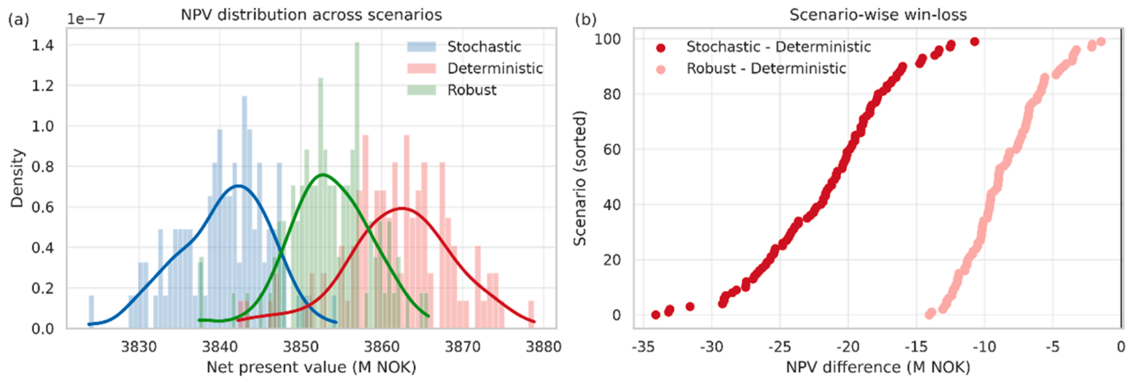

Fig. 4. (a) Distribution of net present value (NPV; M NOK) across scenarios under the stochastic, deterministic, and robust solutions. Histograms and kernel density curves illustrate differences in central tendency and spread among the three approaches. (b) Scenario-wise NPV differences (M NOK) between the robust (pink) and stochastic (red) solutions with the deterministic solution, sorted by magnitude.

values of Γ (Supplementary materials)

The expected harvest shortfalls is presented as the CVaR, which is the mean positive deviations below the periodic timber-supply target (Fig. 5) In the first period, no expected shortfall occurs for any solution, reflecting the emphasis on immediate harvest opportunities to maximize NPV. For the deterministic solution, all subsequent periods experience some level of shortfall. The robust solution represents a substantial improvement, although most periods do exhibit an expected shortfall. On the other hand, the stochastic solution has very little expected shortfall. Readers are reminded that all solutions are applied to a new set of 100 scenarios, which prevents any potential contribution of anticipatory planning from occurring. The average expected shortfall is 0.11 m^3/year (1.9% per year) for the deterministic solution, 0.06 m^3/year (1.1% per year) for the robust solution and <0.001 m^3/year (<0.1% per year) for the stochastic solution.

Compared with the NPV-only case, the timber supply target induced a more pronounced shift in final felling timing . A general pattern to manage uncertainty of periodic even-flow of timber is a reduction of first period harvesting, which is then allocated across all other periods. This causes a reduction in the NPV but enables harvest decisions to be made in a way that better satisfies the requirement for the even-flow of timber (Fig. 6). The adjustments in final felling timing differs between the robust and stochastic solutions, with only minor similarities. Changes under the robust formulation are generally less extreme, whereas the stochastic solution exhibits stronger temporal changes. Both the robust and stochastic solutions reduce harvesting in the first period, but diverge both in the reduction of the first period harvest and how the adjustments are distributed across the planning horizon.

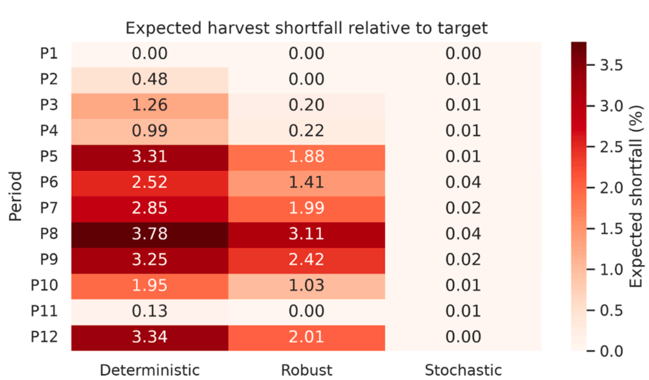

Fig. 5. Expected harvest shortfalls relative to targeted periodic harvest (%). Values represent the mean percentage shortfall below the target for each period and solution (Deterministic, Robust and Stochastic). Darker shades indicate larger deviations below the targets. A value of zero indicates that the expected harvest target is either met or exceeded.

Discussion

This study explores how bark beetle disturbance risk can be incorporated into regional forest planning, with particular emphasis on the reliability of periodic timber supply. This study builds on earlier stand level economic assessment of bark beetle impacts in the boreal forest (Romeiro et al., 2024, 2025), expanding the problem to a larger spatial scale. The results demonstrate the importance of the planning objectives, when managing disturbance risks. When the objective prioritizes maximizing the expected net present value, the benefits of accounting for bark beetle disturbances are small. In contrast, when prioritizing a stable periodic supply of timber, the method to address uncertainty becomes much more important. To support comparison, the formulations were kept as consistent as possible, with the main distinction being how each model treats uncertainty in the periodic timber-flow requirements. The impact of bark beetle damages are explored using a selection of operational research models to integrate risk. We evaluated the three alternative approaches: deterministic linear programming formulation that ignores disturbance risk, a robust optimization formulation that incorporates uncertainty to the constraints using a range of the error to protect the constraints and a stochastic optimization formulation that explicitly represents uncertainty through multiple scenarios. Depending on the specific case, the value in how the risk of bark beetle damage is mitigated will differ. To quantify the impact of using risk measures, we evaluate the stochastic and robust solutions with the deterministic problem as a benchmark.

When prioritizing the economic value of the forest, the benefits of mitigating bark beetle risk are limited. Both the deterministic and robust solutions produce the same solution, as neither directly incorporate the impact of bark beetle damage on the realized economic value of the forest. In contrast, the stochastic approach represents bark beetle damage through explicit scenarios, enabling the effects to be incorporated into the expected NPV calculation and results in a modest increase in expected NPV. This result is consistent with earlier studies, where mitigating disturbance impact to the NPV outcome requires slightly earlier harvest, so that timber can be harvested before damage can occur (Diaz-Balteiro et al., 2014; Romeiro et al., 2024). An alternative risk-averse formulation could be to use the CvaR of the NPV directly in the objective function. This would further reduce the tail distribution of the NPV, however this would result in a modest reduction in the E(NPV), highlighting an explicit trade-off between economic efficiency and risk aversion.

When prioritizing the periodic income from harvested timber, the usefulness of risk measures are substantially more evident. The deterministic model ignores uncertainty, resulting in systematic shortfalls in the periodic timber harvest when disturbances occur (Fig. 5). The robust model performs better than the deterministic case, reducing the

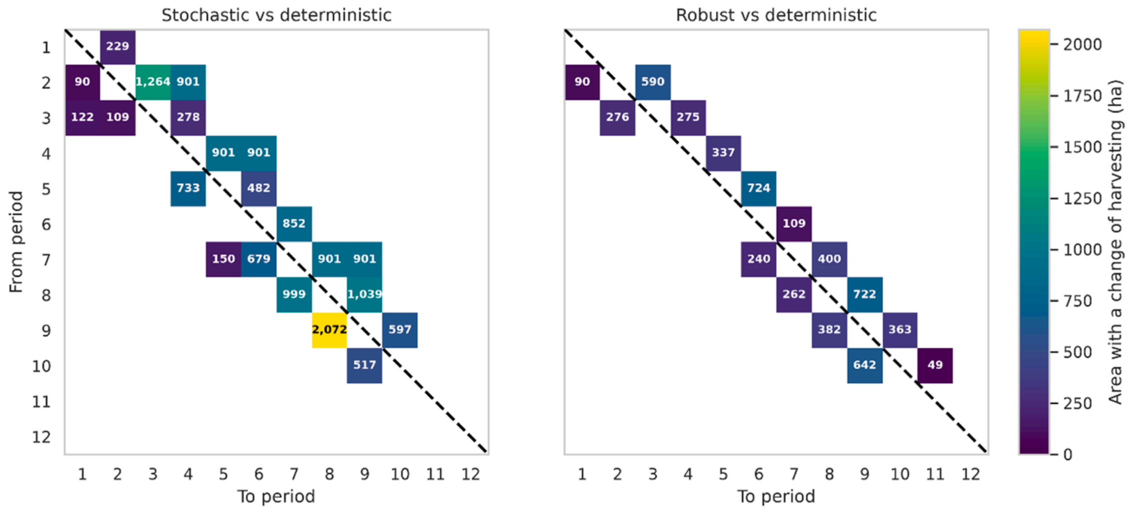

Fig. 6. Changes in the final-felling timing when requiring a specific periodic income. Each cell shows the expanded forest area allocated to management alternatives whose final-felling period changed from the period on the horizontal axis to the period on the vertical axis. Cells below the diagonal line indicate earlier final felling; cells above the diagonal line indicate delayed final felling.

shortfalls in periodic timber harvest (Fig. 5). This is accomplished by effectively assigning a safety margin to increase the planned harvests, depending on the magnitude of the uncertainty. The degree of protection depends on how uncertainty is quantified ($\widehat{I}$) and how conservative the planner chooses to be (Γ). The approach does not address the specific forest dynamics that generate uncertainty and risk.

The stochastic programming formulation addresses uncertainty in a fundamentally different way by representing bark beetle damage through a set of explicit scenarios. These scenarios reflect alternative realizations of disturbance across the region and over time, allowing the optimization to condition harvest decisions on the evolving vulnerability of the forest resource. As a result, the stochastic solution is better able to redistribute harvests temporally to maintain supply reliability across planning periods. The effectiveness of this approach depends on the plausibility of the simulated disturbance scenarios, which in turn relies on the quality of the underlying disturbance model. Nevertheless, even with imperfect foresight, explicitly representing uncertainty enables a closer linkage between forest dynamics, disturbance risk, and operational planning decisions.

A key insight from this study is that the costs observed when accounting for disturbance risk should not be interpreted as losses caused by uncertainty itself, but rather as the cost of reducing downside risk in planning outcomes. When only expected NPV is considered, both deterministic and robust solutions effectively ignore uncertainty, resulting in very minor economic losses. When even-flow requirements are imposed, incorporating uncertainty allows planners to better meet regional timber demand and reduce the likelihood of supply shortfalls, which is often a critical concern for forest industries. While the modeled planning framework is necessarily a simplification of real-world decision-making, it highlights how alternative planning formulations can alter the perceived and realized impacts of large-scale disturbances.

From a management perspective, these findings are particularly relevant for southern Scandinavian forests, where bark beetle disturbances are expected to become more frequent and severe. Even without introducing additional silvicultural adaptations, planning approaches can be adjusted to better anticipate and accommodate the impacts of disturbance. Long-term strategies such as changes in species composition or stand structure operate on time horizons of several decades and are subject to substantial additional sources of uncertainty. In the shorter to medium term, improving planning frameworks offers a pragmatic way to maintain sustainable timber supply under increasing disturbance pressure. While stochastic programming may not be strictly necessary in all contexts, it increases the decision makers potential understanding of uncertainty impacts. As it provides a transparent and flexible tool for integrating uncertainty into regional forest planning and for supporting more resilient decision-making.

Conclusion

This research demonstrates that the implications of incorporating bark beetle uncertainty into a regional forest planning problem depend on how uncertainty is represented and the objectives of management. When prioritizing economic returns (evaluated as NPV) the comparison between the deterministic (and robust) and stochastic solutions indicates that there should be slightly shorter rotations, and a modest shift in the harvest timing. In contrast, when prioritizing the periodic income from the importance of appropriately addressing uncertainty increases dramatically. The deterministic solution leads to systematic shortfalls under realized disturbances, while the shortfalls are less in the robust solution and nearly not present with the stochastic solution. These results demonstrate the trade-off between economic efficiency and harvest stability and clearly presents importance to appropriately address disturbances when planning for the future use of forest resources.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work the authors used the CODEX tool by OpenAI in order to organize and structure the project repository and to refine the README documentation to improve clarity, logical organization, and reproducibility of the code. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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CRediT authorship contribution statement

Kyle Eyvindson: Conceptualization, Formal analysis, Methodology, Visualization, Writing – original draft, Writing – review & editing.

Victor F. Strîmbu: Conceptualization, Methodology, Software, Writing – original draft, Writing – review & editing. **Joyce Romeiro:** Conceptualization, Methodology, Writing – review & editing. **Tron Eid:** Conceptualization, Funding acquisition, Investigation, Writing – review & editing. **Annika Kangas:** Conceptualization, Funding acquisition, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Kyle Eyvindson reports financial support was provided by University of Helsinki. Tron Eid reports financial support was provided by Norwegian University of Life Sciences. Annika Kangas reports financial support was provided by Natural Resources Institute Finland. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Supplementary materials

Supplementary data associated with this article can be found, in the online version, at 10.1016/j.tfp.2026.101415.

Data availability

Data will be made available in a repository.

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