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RESEARCH ARTICLE

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Incorporating stand level risk management options into forest decision support systems

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Abstract

Aim of study: To examine methods of incorporating risk and uncertainty to stand level forest decisions.

Area of study: A case study examines a small forest holding from Jönköping, Sweden.

Material and methods: We incorporate empirically estimated uncertainty into the simulation through a Monte Carlo approach when simulating the forest stands for the next 100 years. For the iterations of the Monte Carlo approach, errors were incorporated into the input data which was simulated according to the Heureka decision support system. Both the Value at Risk and the Conditional Value at Risk of the net present value are evaluated for each simulated stand.

Main results: Visual representation of the errors can be used to highlight which decision would be most beneficial dependent on the decision maker's opinion of the forest inventory results. At a stand level, risk preferences can be rather easily incorporated into the current forest decision support software.

Research highlights: Forest management operates under uncertainty and risk. Methods are available to describe this risk in an understandable fashion for the decision maker.

Additional keywords: risk preferences; forest management; inventory error; value at risk; conditional value at risk.

Abbreviations used: BA (basal area); CVaR (conditional value at risk); DA (data assimilation); DM (decision maker); DSS (decision support system); E(NPV) (expected net present value); LP (linear programming); VaR (value at risk).

Authors´ contributions: Writing and editing manuscript; data processing: KE, RS, LOE. Method development; interpretation of data: KE, RS. Supervision: LOE.

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Introduction

Forest information serves as the basis for the forest planning process. The information allows the use of growth and yield models to predict future states given different management options. However, forest information is not free from errors, and errors in forest information have the potential to lead to suboptimal decisions. To manage these errors, one option is to update the information by conducting a new inventory (Ståhl *et al.*, 1994). Another option is to use the information you have, including the information with the errors inherent in the data. Empirical studies have been conducted which can be used to provide estimates for the quality of the forest information (see Haara & Leskinen, 2009; Mäkinen *et al.*, 2010). To ease the management of updating the information, a recent proposal has suggested the use of the data assimilation (DA) procedure (Ehlers *et al.*, 2013; a part of the data acquisition research). Very simply, the idea is to assimilate new information with the existing information, resulting in better quality information than either could provide separately. The use of this procedure has two main advantages; the first is to reduce uncertainty in itself and secondly to provide an estimate of uncertainty regarding the forest information.

When making decisions for forest management, the use of stand level forest information is essential when making decisions at either a stand or forest scale. Forest scale problems are characterized by the need to simultaneously consider the actions in several stands. This is especially the case when optimizing the even-flow of timber over time. To many forest owners the sophisticated and computationally demanding methods needed for planning at a forest scale are not always motivated. At the forest scale, some studies have evaluated the cost or benefit of improving the data quality with respect to management or data acquisition policies (Duvemo & Lämås, 2006; Kangas, 2010). When considering issues of risk at the forest scale, Eyvindson & Cheng (2016) have compared the issue of maximizing net present value while managing the risk of achieving a specific periodic flow of income. For decisions to be made at the stand scale, the quality of the information available is a major concern. Forest owners may be more interested in making decisions for individual stands. As more than 90% of all forest holdings in Europe encompass 10 or fewer hectares (Hirsch *et al.*, 2007), forest owners may not consider the need to conduct forest scale management. As a result, research has been invested in solving stand level risk and the problems of uncertainty (Pasalodos *et al.*, 2013).

Akin to multiple criteria problems in general, problems which include risk and uncertainty also require the involvement of the decision maker's (DM) preferences. As most forest owners may not be aware of the implications of a decision in terms of risks and uncertainties, the planner must be able to provide easy to understand descriptions for managing risk. While risk and uncertainty have been defined where risk has a known probability and uncertainty has an unknown probability (Knight, 1921), we will use the terms in a slightly different fashion. We will use uncertainty (or estimate of uncertainty) to refer to an attribute of the forest data, and risk is a perception of the DM. Comparing the ability of different decision options to provide a specific result can be done through a variety of risk measures. This could be done using a variety of probabilistic framework models – such as Bayesian theory, scenario analysis, sensitivity analysis and other methods (Pasalodos *et al.*, 2013). In general, measures of risk evaluate any deviation from the desired outcome as unwanted. For instance Markowitz (1952) evaluated risk as the variance of a return from specific portfolio of investments. However, this generalization may not hold true for all DMs, as often the downside effects are of much more interest than the potential positive effects of uncertainty. Risk measurement literature refers to these measures as "downside risk measures" and they evaluate the probability of the occurrence of loss (Nawrocki, 1999). Two common risk measures are the value at risk (VaR; Duffie & Pan 1997), which measures the point where a given probability of loss is exceeded and the conditional value at risk (CVaR; Rockafellar & Uryasev, 2000), which measures the average loss exceeding a given probability.

To make use of the information regarding risk and uncertainty forest planners should integrate it into forest decision support systems (DSS). These systems are designed to support the planning process in a general manner. By providing the initial conditions of the forest, forest growth and yield models predict the development of the forest while optimization models support the forest planners in their decisions. Forest DSS are ubiquitous and exist in all countries where forestry is of some importance (Borges *et al.*, 2014). However, as pointed out by Pasalodos *et al.* (2013), unless the DSS is specially designed to account for a certain risk factor, like fire, wind or insect outbreaks, there are very few systems that incorporate risk management tools, as they operate with point estimates of the initial forest condition and only estimate a single point for growth and yield projections. As a result, the plans created for the DM ignore the uncertainty in the forest information.

In their review Pasalodos *et al.* (2013) discuss several likely causes for this situation. In addition to technical and computational reasons they also direct attention to the idea that the DM may only want unambiguous answers. For a DM, assessing or expressing risk preferences can be difficult and they may feel unaccustomed to the notion of risk and uncertainty. Their conclusion is that "If we actually decide to consider some given uncertainty in our DSS, we need to select methods and tools that are suitable for the decision problem in question and that are sufficiently easy to implement and use. Extremely important is to find ways to communicate the uncertainties to the decision makers…"

When approaching the management of risk, researchers have often used a rather myopic view. Either they focus on simply minimizing the risk (Hahn *et al.*, 2014; Robinson *et al.*, 2016) or they compare the difference between the expected value solution with and without considering uncertainty (Forsell & Eriksson, 2014). By avoiding the potential opportunities for trade-offs between risk and the expected solution, the potential benefits to incorporate sources of uncertainty may seem rather small. The approach we examine here is related to earlier work by Eyvindson & Cheng (2016) where at a forest scale they examine the trade-off between maximizing the expected net present value (E(NPV)) and the CVaR associated with the desired periodic even-flow of timber. For this case, at a stand scale, we examine possible methods for portraying the trade-off between maximizing the E(NPV) and the risk of achieving a specific desired NPV. The use of these methods can be linked directly through the appropriate use of data provided by data acquisition methods (see Saad *et al.*, 2017).

The purpose of this study is to examine methods of incorporating risk and uncertainty through a forest DSS at stand level. By incorporating measures of risk to manage the forest, we expect different decisions to be made at a stand level for risk neutral and risk avoiding DMs. To maximize NPV, we expect that risk neutral DMs should conduct treatments earlier than those DMs that have a risk avoiding preference. The methods are illustrated through a case study by taking uncertainty stemming from measurement errors of the initial state. Two approaches to portray the impact of managing risk are highlighted in addition to the case of evaluating the expected value approach.

Material and methods

Generating data with the DSS

The input data for the DSS consists of a core set of information for each stand (a relatively homogenous area of forest). Depending on the forest DSS, this information can be in a variety of formats; depending on the specific application. The forest information can be represented by average values, diameter classes or tree lists depending on the growth projection model.

If we limit the description of forest DSS to those that incorporate multiple periods and long term planning we can discriminate those that answer 'what-if' questions and those which utilize optimizing systems. The former assesses the consequences of a particular set of prescriptions. Some of them also make stochastic information available through Monte Carlo simulation (see Pasalodos *et al.*, 2013). The latter DSSs find an optimal management of a forest given a set of objectives and constraints, *i.e.* the way the stands or strata should be managed is the result, not the input, of the analysis. It is this kind of forest DSS we will use as a platform for introducing risk and uncertainty information.

In the Forest DSS database of the about 60 forest DSS documented, 12 use linear programming (LP) for planning at the forest scale (http://www.forestdss.org/wiki/index.php?title=Category:DSS). The typical forest DSS using LP for long term planning has a structure depicted in Figure 1, going back to the taxonomy established by Johnson & Scheurman (1977) as Model I or Model II (see also Gunn, 2009). In the preparation of the LP model, a number of different management programs are created for each stand where a management program is a sequence of forest management activities stretching over the entire planning horizon. The creation of the wide variety of management programs is done through a decision logic tree (Siitonen, 1993). To create a variety of plans, slight modifications are made, by delaying or bringing forward some actions. The key treatment options used in the development of the management programs was to conduct commercial thinnings, the final harvest and the required silvicultural activities to ensure the re-establishment of the forest stand. The variety of management programs were used as the input data for the optimization problem. This problem is to select the management program which most accurately reflects the preferences of the decision maker. It is the capacity of the LP adapted DSS to compute a large number of management programs that will be used to give the forest owner risk information, not the LP model *per se*.

The description of uncertainty in most forest applications assumes continuous variables. To be able to use this data in the DSS structure, the underlying estimate of uncertainty needs to be approximated through scenarios. Each scenario represents a realization of possible forest attribute values. The probability for each scenario (posterior) is calculated given the estimate of uncertainty (prior). In other words each estimate of uncertainty is discretized and replaced with several point estimates with their associated probabilities. Kangas *et al.* (2014) and Eyvindson & Cheng (2016) are examples of scenario approaches found in forest planning.

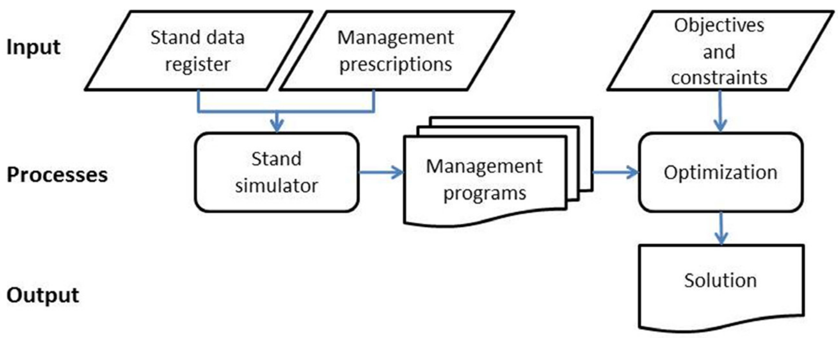

Figure 1. The typical structure of a forest decision support system (DSS) designed according to the Model I or Model II concepts.

Given that the error refers to the initial state, each scenario can be represented as a stand in the DSS. As the data is in the same format as with a single point estimate, this does not require fundamental changes to the structure of the stand management program generating DSS. To generate information about uncertainty with the forest DSS the following steps are followed: (a) the distribution of the stand variable(s) is discretized, where each instance represents a scenario; (b) each scenario is input as a stand (here termed pseudo stand); and (c) a range of management programs over the planning horizon is computed for each pseudo stand.

The key parameter to properly represent the uncertainty is the choice of how many scenarios will be used in representing the true distribution of the uncertainty. In stochastic programming, this has been a key issue of interest, as the tractability of the problems requires as small number of scenarios as possible, while still providing a suitable solution quality (King & Wallace, 2012). For the VaR and the CVaR the number of scenarios must be high enough to allow for the calculations at the specific probability desired.

Expected net present value - E(NPV)

Probably the most proliferous measure involving risk and uncertainty is the expected value. In this case, the maximum expected NPV, defined as

$$\overline{\overline{\mathrm{E}(\mathrm{NPV}_J)}} = \max_{i \epsilon J}[\mathrm{E}(\mathrm{NPV}_i)] \quad (1)$$

where J is the set of management programs and $\mathrm{E}(\mathrm{NPV}_i)$ is the expected NPV of management program i, which in turn is defined as

$$\mathrm{E}(\mathrm{NPV}_i) = \sum_{n \epsilon N} p_n \cdot \mathrm{NPV}_{in} \quad (2)$$

where N is the set of scenarios, p_n the probability of scenario n, and NPV_{in} the NPV of program i under scenario n. The maximum expected NPV can of course be complemented by information of variance as an assessment of its uncertainty.

CVAR / VAR

With each scenario having the same probability, both VaR and CVaR are relatively easy to calculate. For instance, at a 5 % level VaR is equal to the 5th lowest NPV of the set of 100 scenarios, while CVaR is the average of the results lower than the VaR at the specified percentage. In this case, the lowest gains at a specific probability. Put otherwise, there is 1-α probability that the gain will be at least at the level of VaR or that the expected gain will be at least at the level of CVaR.

For this concept, the VaR can be formulated as finding a specific quantile for each management program. Assume that the NPV values for management program j are sorted in ascending order. The VaR for program j at quantile α is then found by

$$VaR(\alpha)_j = \mathrm{NPV}_{jn}\, where\ n = inf_{k \epsilon N}\left\{\sum_{i=1}^{k} p_i \geq \alpha\right\} \quad (3)$$

i.e. $VaR(\alpha)_j$ is the NPV value corresponding to the n^{th} scenario where scenarios 1 to n will sum up to probability α. CVaR is then the average of those scenarios, *i.e.*

$$CVaR(\alpha)_j = \sum_{n \epsilon N} p_n \cdot \mathrm{NPV}_{jn} \quad (4)$$

In the case each scenario is given the same probability n will simply be α*N.

Based on these definitions the optimal management program j* that best balances the risk neutral *E(NPV)* and the risk component (expressed as either VaR or CVaR) is found as

$$j^* = argmax_{j \epsilon J}\left[\lambda \cdot \overline{\overline{\mathrm{E}(\mathrm{NPV_J})}} + (1-\lambda) \cdot R(\alpha)_j\right] \quad (5)$$

where $\lambda \in [0,1]$ represents the tradeoff between maximizing the E(NPV) and ensuring the highest value of the particular risk measure *R(j,α)* where R_j is expressed either as VaR or CVaR at a specified confidence limit α. At one extreme λ=1 results in the management program with maximum E(NPV); at the other extreme λ=0 gives the management program associated with the maximum NPV or maximum expected NPV at confidence level α according to VaR or CVaR, respectively.

The choice of management program thus depends on two subjective parameters, both related to risk awareness. One possibility to ease the task of the DM would be to calculate the optimal programs for ranges of λ at a given α.

Program choice based on DM's personal view on the true basal area (BA)

Rather than relying on numerical analysis, another approach could be used to inform the forest owner would be to see what programs are efficient from the perspective of the uncertain variable or variables. For each scenario the best management program, in this case the program yielding the maximum NPV, would be presented. Put otherwise, the method presents a Pareto front of management programs linked on the property of the uncertain parameter. One benefit would be that it gives the forest owner a visual illustration of the relation between erroneous variable and optimal management program.

Results. Case study

To highlight how estimates of uncertainty can be incorporated into a forest DSS, we provide a small case study with eight stands from Jönköping, Sweden. These stands were inventoried in 2011, using a plot sampling inventory method. The original stands' variables consist of mean values (corresponding to stand register mean values). The selection of the stands was done subjectively, with an aim of having different stands to cover the variety in stand age, different species and site index. The characteristics of the stands can be found in Table 1.

In this study, errors were simulated for basal area value of each stand using the DSS tool Heureka (Wikström *et al.*, 2011). Heureka uses a large set of models to predict the potential future development of the range of forest conditions found in the Swedish forest. The models are based on the single tree approach, while the input data is at a stratum level, tree lists are generated based on estimations of the distribution of trees. Costs related to silvicultural activities and the stumpage values of the trees were based on the recent data. Heureka/Planwise is a forest DSS which generates a number of management programs as input to a LP or mixed integer programming problem. The simulated errors were replicated with 100 scenarios of a normal distribution with mean corresponding to the point estimate and variance 30 % of the corresponding stand's basal area value. This error is on the higher end of the spectrum, especially considering modern inventory techniques and DA. Only a single source of error has been used in this case for illustration purposes; however multiple sources of errors can be considered using a rather similar approach. For each stand, the 100 different pseudo stands were imported to the Heureka DSS and a maximum of 100 management programs were created for each scenario. Only those management programs which were created for all scenarios were considered. This means that for each stand, all scenarios can be managed using the same range of management programs. This was done to properly calculate the expected value, CVaR and VaR of a stand, for these calculations, a 3% discount rate was used. For stands 1–8, the number of management programs was respectively 59, 45, 84, 22, 71, 60, 74, and 87.

The management program with the maximum NPV based on the point estimate (using only scenario 50 – representing the initial stand level data) and the maximum expected NPV program are presented in Table 2. The harvest decisions are different in only one stand (no. 6) out of the eight study stands. However, the differences between the harvesting decisions are not substantial. The suggested management program obtained from the point estimate is to conduct the same actions one period earlier than the management program suggested by the maximum expected NPV program.

Table 1. The key characteristics of the eight stands used in the study

Stand	Basal area (m^2)	Site index (m)	Age	Dominant species
1	30	27	37	Pine
2	20	24	53	Pine
3	16	28	73	Pine
4	27	24	36	Spruce
5	18	31	50	Spruce
6	27	24	53	Spruce
7	43	35	58	Spruce
8	24	22	87	Spruce

Both the CVaR and VaR methods suggest the use of rather similar management programs depending on the risk preferences of the DM (Tables 3 and 4). Nearly all of the efficient management plans suggested are the same, with the CVaR method suggesting two additional plans for stands 2 and 5. Both measures show a tendency to favor longer rotations with increased risk aversion. This shift to longer rotations allows for the stand to grow, reducing the possibility that a stand will be harvested with a relatively low BA, while increasing the possibility that a stand will be harvested while heavily stocked.

Figure 2 presents the management programs yielding maximum NPV for different scenarios, *i.e.* different BA values. For each stand, the 100 BA scenarios were divided into broader intervals where in each interval the dominant management plan is presented. The BA

Table 2. The optimal management plan (F= final felling; T= thinning; number = 5-year period) when using a point estimate and when using a distribution of alternatives. This highlights that similar management programs can be expected when only net present value (NPV) is of importance.

Stand	Point estimate program to maximize NPV	Scenario approach to maximize expected NPV program
1	T3-T5-F8	T3-T5-F8
2	T2-F6	T2-F6
3	F3	F3
4	T2-T4-F7	T2-T4-F7
5	F4	F4
6	T2-F5	T1-F4
7	F1	F1
8	F2	F2

Table 3. The trade-offs between the conditional value at risk (CVaR) with α=0.05 of the net present value (NPV) and the expected NPV for stands 1-8 (F= final felling; T= thinning; number = 5-year period). Only a selection of management plans is Pareto efficient.

Stand	Lambda	Management plan	CVaR (0.05)	E(NPV)
1	[0,0.57)	T3-T5-F9	24887	47781
	[0.57,1]	T3-T5-F8	24726	47905
2	[0,0.08)	T1-F7	13244	32714
	[0.08,0.61)	T1-F6	13187	33405
	[0.61,1]	T1-F5	12870	33608
3	[0,1]	F3	16036	35749
4	[0,0.32)	T3-F6	35079	67471
	[0.32,1]	T2-T4-F7	33958	69904
5	[0,0.18)	F3	32853	66380
	[0.18]	F4	32714	67033
6	[0,0.37)	T2-F6	30509	71383
	[0.37,0.71)	T2-F5	30166	71971
	[0.71,1]	T1-F4	29046	72433
7	[0,0.28)	F2	87314	175797
	[0.28,1]	F1	86054	179094
8	[0,0.07)	F5	16377	38325
	[0.07,0.34)	F4	16298	39462
	[0.34,0.84)	F3	15934	40195
	[0.84,1]	F2	15170	40346

intervals were then selected subjectively based on the list of best programs over the scenarios. Additionally, from Figure 2 it can be noted that for almost all stands the same management programs are suggested by the VaR/CVaR measure. The results from the expected NPV method and the results from the CVaR and VaR can be seen to provide similar management suggestions. The tendency that increased risk aversion implies longer rotations observed for VaR/CVaR is here associated with the expectation of smaller BAs.

Discussion

The results of this study highlight the potential of incorporating estimates of uncertainty into the forest planning process. To be of practical use, tools for managing uncertainty should be integrated into the application of forest DSSs. This allows the DMs the opportunity to consider their risk preferences, such as risk-neutral or risk-averse, and adjust forest management decisions to reflect these attitudes. For instance, if we examine the decisions taken for the second stand, the E(NPV) and the point estimate decision suggests the conduct of a thinning in period two and a final felling in period six. If the DM is risk averse, the option to conduct the final felling in period 7 or 8 may be preferable. Even though the E(NPV) is lower, during that delay the BA will increase and the probability of harvesting the forest with a low NPV is reduced.

The use of most current DSS assumes the analysis is deterministic and the models are run with a deterministic framework. In the example used in

Table 4. The trade-offs between the value at risk (VaR) with α=0.05 of the net present value (NPV) and the expected NPV for stands 1-8 (F= final felling; T= thinning; number = 5-year period). Only a selection of management plans is Pareto efficient.

Stand	Lambda	Management plan	VaR (0.05)	E(NPV)
1	[0,0.13)	T3-T5-F9	28980	47781
	[0.13,1]	T3-T5-F8	28961	47905
2	[0,0.59)	T1-F6	16323	33405
	[0.59,1]	T1-F5	16041	33608
3	[0,1]	F3	19898	35749
4	[0,0.23)	T3-F6	41084	67471
	[0.23,1]	T2-T4-F7	40377	69904
5	[0,1]	F4	38758	67033
6	[0,0.42)	T2-F6	38652	71383
	[0.42,0.71)	T2-F5	38236	71971
	[0.71,1]	T1-F4	37145	72433
7	[0,0.31)	F2	103241	175797
	[0.31,1]	F1	101817	179094
8	[0,0.1)	F5	19727	38325
	[0.1,0.13)	F4	19606	39462
	[0.13,0.86)	F3	19503	40195
	[0.86,1]	F2	18587	40346

this paper, the information about uncertainty added to the DSS through scenarios. Thus, the increase in computational tasks is related to the number of scenarios used to approximate the estimated uncertainty. For this case, only inventory errors have been included. However if the error can be represented in a scenario approach, that error can also be included. For instance, uncertainty regarding the fertility of the specific stand (*i.e.* the site class) could be included through a scenario approach. In earlier research, Eyvindson & Cheng (2016) included inventory, growth model errors and price uncertainty within the simulation process. While all of the forest simulations were conducted in the DSS, the analysis was conducted outside of the DSS. As indicated by Pasalodos *et al.* (2013), this is commonly how risk analysis is conducted with the limited capacity of today's DSS.

To make forest planning under risk and uncertainty more prevalent amongst practitioners analytical tools need to be integrated into the same DSS as other planning tasks. To add the functionality of conducting this type of analysis within the DSS, an applicable software package should be developed. This package should allow for running the same management program for a set of scenarios which incorporates a variety of uncertainty estimates, and should integrate this information for ease of analysis. A scenario approach, as demonstrated here, could be easily implementable in existing DSS. From a programming point of view, the method based on the DM's personal view of the BA is probably the easiest since each scenario, or pseudo stand, can be treated separately, just registering the maximum value program. Probably, the most demanding part is in arranging the visual illustration, where a mechanism for aggregating the programs is needed. The E(NPV) and the CVaR and VaR methods require that a register is held of the simulations over all scenarios for computing the expected value of a sequence of forest activities. Still, the only operation required is to sort the management

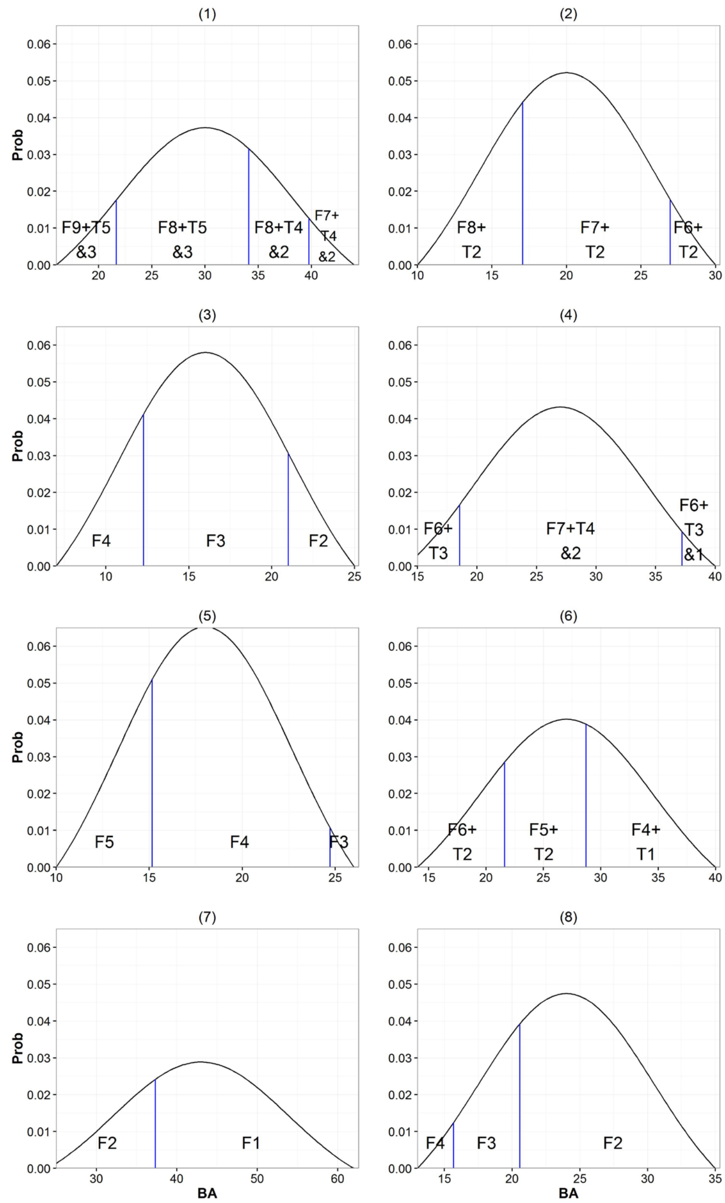

Figure 2. Optimal management plans for different basal areas (BAs) for stand 1-8. F= final felling; T= thinning; number = 5-year period. Risk averse decision makers would select management options which fall below the expected BA, while risk seeking decision makers would select management options which fall above the expected BA.

program according to the criterion of interest (such as NPV).

Risk attitudes and measures can be difficult for forest owners to understand, so it is important that forest planners understand the meaning behind these risk measures. The VaR and CVaR methods provide information regarding the unwanted tail of the distribution. Managing risk is essentially a tradeoff analysis, in this case, between the E(NPV) and the risk of what may happen in the worst cases. Here the trade-off is modeled through the λ parameter, on the one extreme (λ=1) the objective is only focused on the E(NPV), while on the other the objective is focused on the risk measure. All other values of λ represent trade-offs between the E(NPV) and the risk measure. The VaR can be interpreted as at which percentage (α) losses will exceed, while the CVaR is the average of the losses exceeding VaR. For the use of these measures in a multi-criteria context, simplicity in understanding what the measure is may be of utmost importance, and the VaR is simpler to understand than the CVaR (Durbach & Stewart, 2012). However, the VaR is not a coherent risk measure, whereas the CVaR is (Artzner *et al.*, 1999). If risk coherence is of importance to the forest owner, then the use of CVaR could be preferred.

Undeniably, VaR and CVaR can be rather abstract concepts for the typical forest owner. In this respect using the method based on the DM's personal view of the possible errors would seem to offer an advantage. By linking the risk to the forest inventory variable may be easier for forest owners to understand. Most forest oriented DM's can understand measurements of forest properties, however they may find it difficult to understand CVaR or VaR and how it links to forest value. The results displayed in Figure 2 highlight a rather simple way DMs can incorporate elements of risk in the decision making process. This representation allows the DM to select alternative management plans based on their belief on what the 'true' BA for each stand may be.

Both the management proposals selected using the personal view of the DM and those of VaR and CVaR agree with respect to risk (both approaches suggest prolonged rotations with increased risk aversion). The graphics created based on varying the potential personal view of the DM should promote an understanding that there are different management options for managing the forest and they depend on the DMs risk preferences. Thus, the comparative advantage could relate to its pedagogics rather than to its analytical strength. Referring to the latter, it is easy to highlight the shortcomings. One problem is the need of the forest owner to have some idea of the likely state of the stand that is different from the standard density function (if the forest owner is satisfied with the density function risk level can be set by VaR and CVaR). Not all forest owners will be able to consider the inventory state of their forest. Another problem relates to make the illustration convincing when there is more than one source of uncertainty. Evaluating multiple sources of uncertainty would require presenting the figure in multi-dimensional space, or may require some form of interactive process to allow for an evaluation of the risks. A related problem is when moving from stand to forest level planning, as interactions between stands become important. For some of these cases the *E(NPV)*, CVaR or VaR would be more appropriate

One assumption made with the VaR and CVaR methods is that the DM is risk averse. This assumption has not been made with the *E(NPV)* or when providing options based on the personal view of the DM method. Due to this shift in assumption, the *E(NPV)* method suggests management programs a risk seeking DM may select. If we compare the results from stand 1, the same management programs are suggested, if the DM believes that the BA will be lower than the inventoried value. To account for risk seeking preferences, we can adjust the VaR and CVaR method assumption by simply evaluating the opposite side of the tail (this adjustment requires a few minor adjustments to the calculations).

For this case, only economic considerations were evaluated. While this may be a very important aspect for a large proportion of forest owners, the application of risk management can also be applied to ecological considerations As there are a variety of ecological indicators that can be modeled using basic stand level forest information (Mönkkönen *et al.*, 2014; Peura *et al.*, 2016), the risk associated with these values could also be considered. As these indicator values may not be familiar to the DM, special guidance may need to be given towards both understanding the ecological importance of the indicator, and the meaning behind the attached risk measure.

The aim here is to present simple ways of augmenting a common type of DSS with risk management tools, so that such analysis is made more accessible. We have illustrated this with the uncertainty associated with the initial state of the individual stand. There are some rather obvious ways to continue this research. One is to put the methods in actual planning situations. This would give information on how the methods were understood and used. The research could rely on methods in computer science like interactive design (Cooper *et al.*, 2007). Another line of investigation would be to assess for which cases the issues of risk and uncertainty are of utmost importance. Some studies indicate that the point estimate strategies under some conditions fare well compared with risk adapted decisions [climate change (Eriksson *et al.*, 2012), wind throws (Forsell & Eriksson, 2014), and fire (Ferreira *et al.*, 2014)]. This should involve how different risks mix with risk preferences. For instance, prolonging rotation to avoid inventory risk may increase risk exposure to wind throw risk. Yet another area is forest level problems which add another degree of complexity and, subsequently, other demands on the DSS as well as the forest owners' conceptual prowess.

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