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5 **Guidelines for risk management in forest planning – what is risk**
6 **and when is risk management useful?**

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18 **Abstract:**

19 Managing forest resources occurs under various sources of uncertainty. Depending on the
20 management problem, this uncertainty may have a substantial impact on the quality of the
21 solution. As our knowledge on the sources and magnitude of uncertainty improves, integrating
22 this knowledge into the development of management plans becomes increasingly useful, as
23 additional information can improve the decision making process. This adjustment requires a
24 fundamental shift in how planning problems are viewed: instead of interpreting risk management
25 as a technique needed only for addressing problems with natural hazards, risk management
26 should be an integral part of most planning problems. Managing risks can be linked to a variety
27 of adaptive planning methods: to help mitigate risk, plans should either be revised as new
28 information becomes available or the possibility of adaptation should be accounted for in
29 preparing the plans. We conduct a brief examination of the key topics in risk management and
30 highlight how risk management implies trade-offs. Several decision problems which incorporate
31 risk management are analyzed and alternative perspectives for the problem are suggested to
32 better address risk management issues. We then provide a decision framework for considering
33 how to integrate risk management practices into the forest planning process.

34 **Keywords:** Risk Management, Risk, Uncertainty, Conditional Value at Risk, adaptive planning

35

36 **1. Introduction**

37 Making decisions on how to manage a forest holding is a process done with imperfect
38 information. The information regarding the current resources of a forest holding is an estimate
39 that can be subject to substantial uncertainty. To create forest plans, the potential future resources
40 are predicted utilizing imperfect forest growth models. In addition, the future is never certain and
41 local growing conditions may be substantially different than those assumed in the models.
42 Climate change (Garcia-Gonzalo et al. 2016) introduces additional uncertainty to the predictions
43 of growth and survival. Natural hazards can considerably impact the quantity and quality of
44 forest resources (Hanewinkel et al. 2011, Diaz-Baltiero et al. 2014). The economic situation of
45 managing and utilizing forest resources can change quickly and dramatically over time. For
46 instance, timber prices reflect the requirements of the industry, and changes in either demand or
47 supply will cause a change in price. Costs associated with forest management (i.e. silvicultural
48 activities) may change depending on the cost of labour or the development of new technology.
49 Additionally, the political context can introduce uncertainty through the proposition of changes
50 to legislation, or through the introduction of conservation strategies.

51
52 In forest planning, many of these sources of uncertainty are ignored as inconsequential, due to
53 the traditions of planning or overconfidence on the accuracy of the models used. For instance,
54 modern forest inventory methods and growth and yield models are seen as adequate enough for
55 the task, representing the best tools we have now. In deterministic planning the effects of such
56 small uncertainties remain unacknowledged and therefore also underestimated. The decision
57 makers thus see no need for addressing the uncertainty in planning, except for the natural hazards.
58 However, even though the growth models are of high quality, uncertainty introduced by these

59 models can increase costs substantially (Borders et al. 2008; Holopainen et al. 2010; Pietilä et al.
60 2010). Our knowledge on the nature and magnitude of different sources of uncertainty is
61 improving, and integrating this knowledge into the development of management plans should be
62 an essential consideration in forest management planning.

63

64 The concepts of uncertainty and risk have a long history, and the clarification of differences
65 between these two terms has been defined by Knight in the early 20th century (Knight 1921). The
66 separation made by Knight was based on whether the probability distribution of possible
67 outcomes is known (Risk) or not known (Uncertainty). In most natural systems, the precise
68 knowledge of a probability distribution is not possible to obtain. However, through the use of
69 statistics there is a possibility to estimate the probability distribution. If we can estimate the
70 probability distribution of the outcome, we can use risk management tools. In this discussion,
71 we will use the term ‘uncertainty’ to refer to the quality of the information, and the term ‘risk’ to
72 refer to the potential of meeting the goals and expectations of the management plan, or the
73 probability of loss due to natural hazards (see Kungwani 2014).

74

75 Management decision proposed in forest management plans should not be seen as unchangeable;
76 rather the decisions should be adaptive (Yousefpour et al 2012). Very simply put, adaption can
77 occur whenever new information becomes available. Such new information can be revealed
78 when circumstances change due to unexpected events (i.e. Black Swan events (Taleb 2007)).
79 Adapting to events that cannot be predicted (unknown uncertainty) cannot be planned for in
80 advance, and require re-planning based on the updated circumstance. Whenever we have
81 knowledge on the probability of possible outcomes, it is also possible to plan for adaption. New

82 information can be obtained based on planned information collection (e.g. forest inventory), or
83 revealed in time (e.g. expected policy shifts or changes in prices of timber). It is possible to link
84 risk management needs to the specific timing of these events.

85

86 The actions taken to manage risk depend upon which risk element(s) is (are) to be managed. For
87 instance, the management of wind damage can be accomplished through adjustments to the
88 spatial patterns of harvesting (Heinonen et al. 2011). The severity of fire risks can be managed
89 by removing fuel from the forest. Climate change is assumed to increase the growth of trees but
90 also to increase the mortality of some tree species due to e.g. the increased probability of drought
91 during summer or the increased probability of sub-zero temperatures after an earlier start to the
92 growing season. Then, a subset of the impact from climate change can be mitigated by tree
93 species and provenance selection (Forsius et al. 2013). The impact of growth model errors can be
94 removed through the updating of information by conducting a new inventory (Eyvindson, Petty
95 and Kangas 2017). The uncertainty related to inventory errors can be managed by using the best
96 inventory method available. As inventories can focus on different aspects of forest attributes, the
97 best inventory method will depend on the specific management objectives. When we cannot
98 reduce the uncertainty, we can still prepare for it in the decision making.

99

100 Risk management is typically associated with natural hazards that introduce high losses with a
101 low probability. However, risk management is advisable also in cases with high probability of
102 small losses. For instance, climate change may increase the probability of mortality, this may be
103 mitigated after clear felling by modifying the species / provenience selection for regeneration. In
104 risk management, the problem formulation (and the interpretation of the constraints) is of more

105 importance than the source of uncertainty. Deterministic forest planning is often designed to
106 meet a set of constraints, but when the plan is implemented small violations of constraints are
107 acceptable. Introducing risk management into the planning problem will force the managers to
108 consider how important it really is to meet the constraints. Therefore, including risk management
109 in forest planning will make forest planning closer to real-life decision making. This adjustment
110 requires a fundamental shift in how the planning problems are viewed: reflecting how
111 unexpected occurrences are managed in practice, allowing for the efficient handling of the
112 deviations.

113

114 The objective of this paper is to provide guidance for integrating risk management into the forest
115 planning process and a conceptual framework for selecting the most appropriate method for
116 managing those risks in forest management planning. We show that introducing risk
117 management properly into the planning process improves the decisions with reasonable effort.

118

119 **2. Integrating risk management into forest planning**

120 **2.1 Measuring risk**

121

122 The common feature of risk management is that specific attributes of the distribution of the
123 outcomes can be measured and altered through varying the proposed decisions. In a very general
124 sense, the measurement of risk relies upon the evaluation of the specific attributes of the
125 distribution of the potential outcomes of the proposed management actions. One of the first risk
126 measures used is variance. As a risk measure, variance simply evaluates the spread of the results
127 from the expectation value. By measuring the spread, both outcomes which fall short or exceed

128 the expectation value are considered unwanted. As such, the preferential interpretation of this
129 risk measure is one where any variation away from the target is undesirable.

130

131 The late 1950's saw the introduction of downside risk measures, specifically the below mean
132 semivariation (Markowitz 1959). Below mean semivariation (or downside mean semivariation),
133 focuses on the unwanted deviations from the mean. From a dataset of possible outcomes, those
134 values which fell below the mean (or specific target) were included in the evaluation of the semi-
135 deviation. In the late 1990's, the risk measure of the Value at Risk (VaR) was developed.
136 Following the development of the VaR, a related measure called the Conditional Value of Risk
137 (CVaR) was developed by Rockafellar and Uryasev (2000).

138

139 Both VaR and CVaR focus on evaluating aspects of the tail of the distribution of possible
140 outcomes. The CVaR evaluates the average loss exceeding the VaR, while VaR provides the
141 minimum (threshold) loss with a given probability. VaR thus means that the minimum threshold
142 is exceeded with the given probability. As a measure of risk, the VaR is well known in financial
143 markets, and is established in policy documents (BCBS 2004). However, unlike the CVaR, the
144 VaR is not a coherent measure of risk (Artzner 2002). Additionally when minimizing risk, the
145 CVaR can be transformed into a rather simple linear program and optimized, while the VaR
146 requires the use of integer programming.

147

148 In a forest management planning context, a variety of different risk measures have been applied.
149 Robinson et al. (2016) minimized the variance of timber harvested. The shift in the variance of
150 timber harvested involved an (implicit) trade-off in the form of an increase in the amount of

151 forest area harvested. To evaluate the impact of managing risk on the even-flow of timber
152 products, Hahn et al. (2014) evaluated the differences between maximizing the net present value
153 (NPV), the maximization of the certainty equivalent (a return without risk that is equivalent to
154 the uncertain return with risk) of the NPV and the maximization of the VaR of the NPV. To
155 address the management of risks other than in the NPV, namely the negative deviations from a
156 targeted even-flow, Eyvindson and Kangas (2016) used a downside risk measurement and
157 Eyvindson and Cheng (2016) used the CVaR concept. To address both the risk of achieving a
158 minimum targeted income flow and minimum biodiversity protection Hartikainen et al. (2016)
159 used the VaR concept in a multi-objective forest management case. In this case, the trade-off
160 with the objective function value was explicitly shown. For further information on risk measures
161 for forest investments, readers are directed to Hildebrandt and Knoke (2011).

162

163 **2.2 Trade-offs for risk management**

164

165 Introducing risk measures into a planning problem means introducing a new objective(s) in
166 addition to the original one(s), which makes risk management inherently multi-objective. Thus,
167 the management of risk should be seen as a multi-objective planning problem, where the intent is
168 to minimize the negative impacts due to uncertainty, while maximizing the benefits of managing
169 the forest for the decision maker (i.e. society, industry or forest owner). These decision makers
170 may consider specific uncertainties to hold more importance. A wide variety of uncertainties
171 could be of interest to decision makers, as examples: natural hazards, economic uncertainty,
172 future supply requirements, and conservation uncertainties. For instance, forests held by mills
173 may focus on ensuring continual supply, investment holding companies may be sensitive to

174 income from the holding and community / governmental held forests may need to consider a
175 wide range of perspectives. Additionally, the size of the estate owned will impact the perceptions
176 towards risk and management issues (Boston et al. 2015).

177

178 Risk management has often been seen as a single objective optimization problem where the costs
179 of managing the risk is included in the optimization process and a preference towards risk is
180 either assumed or set. From a multi-objective perspective, the trade-off is explicit; more
181 protection from risk will be associated with a loss in the achievement of the other objectives. For
182 the single objective optimization case, analysis of the trade-off between the willingness to accept
183 risk and other benefits are not possible. For those cases when the risk preferences of a decision
184 maker are explicit, the use of a single-objective optimization perspective can be justified.

185 However risk preferences are domain and problem specific (Charness, Gneezy and Imas, 2013),
186 and elicitation techniques may not provide estimations which have enough precision to be used
187 as a parameter of optimization problems.

188

189 Managing the risk associated with decisions is always linked to some cost, either the cost to
190 minimize risk, or the cost of accepting risky outcomes; efficiently managing risk strives to
191 minimize this cost. One way to make management actions less risky is to collect better quality
192 information. For instance, if new information enables us to narrow down the range of potential
193 climate warming from, say, 1° - 4° to 1° - 2° , it would markedly reduce the risks of (monetary)
194 losses related to tree species selection after regeneration. Likewise, better information on the
195 future growth of a stand would reduce the risks of (monetary) losses related to harvest timing.
196 While the improved information will reduce one or more aspects of risk (or provide an improved

197 quantification of the risk), the cost of acquiring new information may exceed the potential
198 benefits. If the benefits of the new information do not exceed the costs of the information, then
199 the objective value will be degraded rather than be improved. Thus highlighting the need to
200 conduct a trade-off analysis also with respect to acquiring new information.

201 One way to evaluate the benefits is through the evaluation of the value of information, measured
202 as the value of improving the quality of information or of including the possibility to collect new
203 information (for example chapter 4 of Birge and Louveaux 2011). In a way, this type of analysis
204 can be compared with the cost plus loss evaluation (Eid et al. 2004, Kangas 2010). In a cost plus
205 loss analysis, the benefits of collecting new information can be linked to the losses of the (old or
206 new) information compared with perfect information. In forestry, this has been applied using a
207 max NPV approach at the level of a single stand (Eid et al. 2004). When moving from a stand
208 level to a forest holding or landscape level, approaches to evaluate the value of the information
209 should be made using the same scale at which the decision is to be made. The value of
210 information relates to how the problem is structured, for multi-objective problems the value of
211 information will also consist of multiple objectives, and may not simply relate to a monetary
212 term. In a multi-objective decision problem, the value of information can be interpreted as an
213 improvement in the objective function value (Kangas et al. 2010, Birge and Louveaux 2011). On
214 the other hand, in many cases just including the uncertainties into the decision problem through
215 stochastic programming will improve the decisions. For instance in a case of inventory errors
216 this improvement can be even larger than the improvement obtainable by collecting additional
217 information, meaning that information on the uncertainty is in itself valuable (Eyvindson and
218 Kangas 2014).

219

2.3 Risk preferences

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Risk preferences identify the willingness of an individual to accept risk. While risk preferences represent a continuum, they are often segregated into three categories: risk averse, risk neutral and risk seeking (Hillson and Murray-Webster 2007). In portfolio management, the acceptability of higher risk relates to the potential for higher profits. Thus, the decision maker needs to address the trade-offs between expected profits and the safety of obtaining the profits. This is called “risk attitude”. A risk neutral person weighs the different outcomes only with their probability, whereas a risk seeker gives a larger weight to the high end of outcomes and the risk averse person assigns a higher weight to the low end of the outcomes (Jarrow and Zhao 2006). One method of defining risk attitudes of a specific decision maker can be done through choice decisions (certainty equivalent, Raiffa 1968). The specific risk preferences are calculated through the presentation of a variety of gambles to a decision maker, and where they are asked the minimum amount they would accept to forgo the gamble.

The elicitation of risk preference from a decision maker provides a snap-shot of the preferences at one point in time. As with all other preferences, risk preferences will change over time and are related to other factors in the decision maker’s circumstances. For instance, a forest owner, a younger owner may have a higher tolerance to risk than an older owner. These changes can be addressed through collecting new information on the risk preferences from time to time and re-planning if the attitude has changed.

242 By utilizing risk measures, the trade-off between the risk objectives and the other objectives of
243 interest are made clear. These trade-offs occur irrespective if we are viewing the problem of a
244 single stand or a landscape; and for different time horizons. Decisions made to reduce the risk
245 with respect to one objective may negatively impact other objectives of interest which hold
246 importance for the decision maker. If no improvements can be made to the risk measures without
247 impacting the other objectives, an active choice by the decision makers must be made.

248

249 Making risk management explicit is always recommendable: it enables the managers to see if the
250 proposed actions for risk management improves or worsens the outcomes of the decision in the
251 planned way. If the costs of risk management appear unexpectedly high or low, the reason may
252 be in flawed decision model, for instance inappropriate measures for the risk or unnecessarily
253 strict constraints. Thus, calculating the trade-offs explicitly also enables the modellers of the
254 decision problem to see if the analysis is useful.

255

256 This trade-off was highlighted in portfolio management in finance in the middle of the 20th
257 century (Roy 1952; Markowitz 1952). These researchers highlighted trade-offs required between
258 maximizing the expectation value of a portfolio and ensuring a specific level of the mean-
259 variance ratio. Depending on the specific problem formulation, similar trade-offs between risk
260 and return (biological or economic) can be found.

261

262 **2.4 Linking risk management to specific decision problems**

263

264 The modelling of a particular decision problem requires the selection of specific alternatives
265 among several options. These modelling choices influence how risk and uncertainty can be
266 integrated into the problem. Depending on the method used to solve the problem, some of the
267 modelling choices are made implicitly. For a review of methods used to introduce uncertainty
268 into forest planning readers are referred to Pasalodos-Tato et al. (2013). For some of these
269 methods there may not be a mechanism to estimate the impacts of risk into the problem (such as
270 the size and frequency of losses), there may be no mechanism to adjust how the feasibility of a
271 solution is interpreted (is a problem still acceptable if the constraints are only slightly exceeded)
272 or the incorporating the risk preferences may not be possible.

273

274 While the calculation of risk measures is not a requirement of managing risk (i.e. Robust
275 programming (Palma and Nelson 2009) or Markov chain models (Buongiorno and Zhou 2017)),
276 the use of risk measures can assist the decision makers by allowing for a trade-off analysis.
277 Introducing elements of uncertainty into the decision problem requires special attention to the
278 interpretation of constraint feasibility. For instance, the direct use of deterministic even-flow
279 constraints under uncertainty will be interpreted as a strict requirement for a minimum flow. In a
280 stochastic setting, such constraints are likely to have a large, negative effect on the objective
281 function value. Thus, appropriate changes need to be made to these constraints, for instance, the
282 threshold may be made fuzzy (Mendoza, Bare and Zhou 1993), based on a specific probability
283 for exceeding the constraint (Bever 2007), or through specific risk measures (such as VaR and
284 CVaR).

285

286 If the uncertainties are not incorporated into the model in a way appropriate for the particular
287 problem, the resulting decisions may be worse than without risk management. Special
288 consideration should be given to how feasibility issues frame the problem: constraints that can be
289 described as goals rather than constraints need to be modelled as goals, and only constraints that
290 really need to be met in every condition should be modelled as strict constraints that are typical
291 in deterministic setting. One example of appropriate strict constraints may be ecological values
292 which should be managed with a strong sustainability perspective (Neumayer 2003); for instance
293 maintenance of biodiversity values above a specific limit.

294

295 The value of managing risk is strongly linked to the risk preferences of the decision maker. For
296 risk neutral decision makers, the value of assessing and managing risk may be rather small. For
297 risk averse decision makers, the value of managing risk can be substantial. Thus, assumptions
298 about risk preferences should be avoided as the potential value of incorporating uncertainty can
299 be lost. At an individual forest owner level there is substantial value in appropriately determining
300 the risk preferences of the owner (Eyvindson and Kangas 2016). For landscape level planning,
301 biodiversity and ecosystem services may be important aspects when conducting management
302 actions. The risk of poor performance in either biodiversity or ecosystem services may be
303 especially undesirable, especially when considering the issue through a strong sustainability
304 framework (Luckert and Williamson 2005). Thus, if assumptions of risk preferences must be
305 made, they should be made with care and should still reflect the desires of the decision maker.

306

307 The possibilities to manage risk also strongly depend on the available management options for
308 the decision makers. The modelling of forest management problems often use “schedules” to

309 identify a single set of possible actions available to be conducted at the forest stand level
310 (Johnson and Scheurman 1977). For each stand, a range of different schedules are simulated to
311 reflect the alternative sequence and timing of forest operations. As new methods of conducting
312 forest operations are developed with a focus on managing risks (i.e. wind or fire), the set of stand
313 level schedules should be updated.

314

315 The relevance of the specific types of uncertainty may hold a variable importance dependent on
316 the spatial and temporal scales of the decision making process. For a private forest owner, short
317 term price uncertainties may be a key concern for near term decision making while uncertainty
318 related to the potential growth may be of greater importance for longer term decisions.

319 Additionally, risk preferences of a decision maker fluctuate over time, and the need for re-
320 planning options may hold value to specific decision makers. On a national scale, the price
321 uncertainty may hold little importance, as the focus may be on ensuring the general sustainability
322 through changing market drivers and the impact of climatic changes. In a recent review,
323 Yousefpour and Hanewinkel (2016) highlight the deep uncertainty of climate change, and the
324 potential for portfolio diversification and robust decision-making to address the associated risk.
325 Diversification of kinds of forests in a region is better adapted for a wider range of climatic
326 conditions (Knoke et al. 2005), and robust decision-making suggests management alternatives
327 which ensure the health and productivity of the forest for the majority of the worst case future
328 scenarios (McInemey et al. 2012).

329

330 For regional scale planning, it is possible that neither price uncertainty nor growth rate
331 uncertainty due to a changing climate may hold critical importance for risk management.

332 Regional level planning often focuses on the near term planning problems (next 5 – 10 years),
333 and the key element of uncertainty may be the quality of the inventory information. As saw and
334 pulp mills require a rather steady flow of specific assortments of timber, uncertainties relating to
335 the harvesting and transportation scheduling play an important role in management of risk. The
336 origin of these uncertainties could relate to near term climatic change, with changes in
337 precipitation intensity (resulting in a higher number of road washouts), or a shorter period where
338 the soil is frozen to allow harvesting activities on sensitive soils. Issues of timber prices are
339 important for procurement managers, as a means to decrease costs. However an unscheduled mill
340 closure (or slow down) due to limited timber supplies may not be an acceptable risk.

341

342 Selecting which species to use when regenerating a site is a decision which must be made under
343 deep uncertainty. Considerations need to be made regarding how well the species will grow
344 under a wide range of potential climatic conditions. This can be complicated by a lack of
345 silvicultural knowledge at specific geographical locations (Lawrence 2017). Additionally, there
346 is the consideration of the expected demand for different timber resources when the newly
347 planted site is ready for harvesting. For short term management problems, our recommendation
348 would be to include a decision rule to determine species type for regeneration, such as a
349 probabilistic decision rule, rather than optimization techniques. For this case scenario analysis
350 may be of value, where the uncertainty is too difficult to integrate into the optimization model
351 completely.

352

353 If it is possible to model the site specific development (including climate change) of the different
354 candidate species, a scenario analysis may be possible (Blythe and Young 1994). One method of

355 coming to a decision is through reflection on which scenario the decision maker believes to be
356 most likely. The solutions selected through this kind of decision making process may not be
357 optimal, as information critical to the process may not be included when finding a solution
358 (Wallace 2000). A related example to the species planting is the crop selection problem in
359 agriculture. This problem highlights the differences between maximizing expected net profit and
360 maximizing the conditional value at risk for a specific risk parameter (Filippi, Mansini and
361 Stevanato 2017). Comparing the optimal solutions, as risk aversion increases, the diversity of
362 crops selected is increased, highlighting the benefits of diversification. Interestingly, compared
363 with what actually occurs, the crops selected by real farmers reflect the very risk averse solution
364 provided by the model (Filippi, Mansini and Stevanato 2017). This agricultural case highlights
365 one method which could be applicable in forestry for deciding which species (in which
366 proportions) to plant in order to manage risk, and this information could be used as the
367 probabilistic decision rule.

368

369 **2.5 Decision problems examples:**

370 To highlight that risk management can be viewed from a wide variety of perspectives, and to
371 communicate the potential for risk management we examine a selection of three published
372 examples of risk management in forestry. We will first quickly describe each example, highlight
373 the methods used to manage risk, and discuss possible improvements for how each particular risk
374 could be managed. The first example is from Hahn et al. (2014) which compares solutions
375 between maximizing either the E(NPV), the certainty equivalent (CE) of NPV or the VaR of
376 NPV. The second example is from Forsell and Eriksson (2014) where they evaluate the impacts
377 on the E(NPV) when striving to manage the wind damage. The third example is from Eyvindson

378 and Cheng (2016) where they evaluate the trade-off between the E(NPV) and the CVaR of
379 obtaining a pre-set target for periodic incomes. While all examples use NPV as the objective of
380 primary interest, it is important to note that risk management can focus on a much wider range of
381 objectives.

382

383 The first example from Hahn et al. (2014) presents a detailed study which compares the E(NPV),
384 CE of NPV and VaR of NPV. These objectives can be seen as a risk measures, as each objective
385 represents a different attitude towards risk. In the analysis, they consider both production and
386 timber price risks, using the YAFO optimization model (Härtl et al. 2013). This approach
387 identifies the optimal timing to conduct thinnings or final harvests for each stand. The results
388 highlight a trade-off between the E(NPV) and the standard deviation of NPV. For the extreme
389 cases, maximizing either E(NPV) or VaR of NPV using a discount rate of 1%, a cost of 2% (i.e.
390 a change from 23,858 €/ha to 23,370 €/ha) of the E(NPV) allowed for an improvement of the
391 standard deviation by 34% (2,238 €/ha to 1,475 €/ha). The authors of this study indicate their
392 surprise at these results. Rather than comparing the improvement of the standard deviation, the
393 authors should have compare the VaR of NPV between the solutions. These results were not
394 provided directly in the article, however it can be calculated using the E(NPV) and the standard
395 deviation of the E(NPV). When the objective function is to maximize the VaR, the improvement
396 in the VaR of the NPV was 6% (from 18,651 €/ha to 19,938 €/ha) while the deterioration in NPV
397 is 2%. To improve the clarity of the trade-off between the E(NPV) and the VaR, it is important to
398 examine the values which were used in the optimization. In this case, the trade-off between these
399 values becomes much less dramatic.

400

401 The adjustments that could be made to the Hahn et al. (2014) approach would be to increase the
402 management options used in the analysis. The management options used in the study were rather
403 limited, including only two decision options (to conduct either a thinning or a final felling). The
404 inclusion of other management options which reduced the risk of hazards would have most likely
405 impacted both the E(NPV) and VaR of the NPV positively.

406

407 The second example of Forsell and Eriksson (2014) evaluates the potential benefit from
408 managing wind risk. No specific risk measure has been used in this example, rather their
409 intention was to evaluate the perceived benefit towards integrating wind risk management for a
410 risk neutral decision maker. This was done by examining the differences in E(NPV) when wind
411 risk was addressed in the optimization model and when it was not. The authors used a graph
412 based Markov decision process framework to find the optimal policy to maximize E(NPV). The
413 risk of wind damage was evaluated using the tool developed by Olofsson and Blenow (2005),
414 and it provided a stand specific probability of wind damage. By using this specific Markov
415 decision process, the authors made an implicit decision to utilize preference of a risk neutral
416 decision maker. The results indicated an improvement of less than 2% to the E(NPV) when wind
417 risk was included.

418

419 A potential improvement for this analysis could be to include risk preferences other than simply
420 a risk neutral preference. While technically challenging, risk aversion is possible using a Markov
421 decision process (Ruszczynski 2010). By incorporating the risk preferences, it could be expected
422 that there would be a higher use of management options which limit wind risk. This higher usage
423 would be visible as improvements in the risk measure.

424

425 The third example from Eyvindson and Cheng (2016) evaluates the trade-off between the E(NPV)
426 and the CVaR of obtaining a specific target for periodic income. For this case, a stochastic
427 programming model was developed which included estimates of uncertainty relating to growth,
428 inventory measurements and the price of the assortments of timber. By evaluating two different
429 components of forest management (i.e. the NPV and the periodic income requirements), the
430 trade-off between these components has a rather large span, and the use of specific risk
431 preferences can produce rather different solutions. This approach avoids considerations of the
432 variability in the NPV and limits the periodic income requirements to reflect an even-flow of
433 income. Using a 3% discount rate, the range of the E(NPV) was between 350,000€ and 360,000€
434 while the aggregated CVaR of the periodic incomes ranged between 5,000 and 45,000€. This
435 example demonstrates the importance of evaluating the trade-off using the values from the
436 objective function. Additionally, this clearly communicates the potential trade-offs between the
437 competing objectives. The changing risk attitudes can be seen clearly in the trade-off curve,
438 increasing risk aversion for not achieving periodic incomes reduces the NPV.

439

440 This approach could be improved by directly eliciting the parameter settings from the decision
441 maker. For this case, the specifics of the decision problem were set in advance, easing the efforts
442 required for the trade-off analysis. For a specific decision maker, a single forest management
443 plan is required, and this could be discovered through an interactive decision process. Through
444 the interactive decision process the parameters of the model could be re-defined, and each time a
445 new solution could be made available (Miettinen and Mäkelä 2000). As the decision maker

446 reflects and learns about the potential outcomes, the forest plan can be expected to be more
447 suitable.

448

449 **3. Guidelines for managing risk in forest planning issues**

450 When planning to manage risk, the focus should be on the value provided to the decision maker.
451 From an application specific perspective, risk managed along a continuum from comprehensive
452 risk management to adaptive planning. Comprehensive risk management can involve techniques
453 which are computationally demanding, thus managers should be able to match the techniques
454 available to the specific case. To ease the computational burden, forest planning researchers need
455 to focus on identifying methods which capture the various sources of uncertainty in as
456 parsimonious fashion as possible. In this way, the sources of uncertainty which are important to
457 the decisions to be made can be incorporated into the planning model. Adaptive planning can be
458 less computationally burdensome, as questions related to how to manage risk are delayed until
459 specific events are observed to have happened. Alternatively, adaptive planning could be more
460 cognitively burdensome, as the decision maker should remain aware of planning situation.

461

462 **3.1 Comprehensive risk management**

463

464 Developing a comprehensive approach to risk management requires a thorough understanding of
465 the uncertainties involved in the forest management problem. The ability to manage specific
466 types of risk depends upon the time horizon under consideration as well as the spatial scale
467 involved. While incorporation of a majority of risk elements may be theoretically possible, the
468 computational requirements and decision process underlying the problem may not require
469 addressing the various risks simultaneously. Some risk can be managed independently (i.e. the

470 choice of which species used in regeneration) and can be integrated into the planning process of
471 other problems. Additionally, the importance of different risks depend upon the stakeholders
472 involved in the decision making process. For a forest holding, a single forest owner may be
473 interested in a very narrow interpretation of risk. At a regional scale, the set of stakeholders
474 involved in making decisions may need to consider a wider variety of risks. Being able to
475 manage risks requires both an understanding of the uncertainties involved, and an understanding
476 of how the decision maker wishes to manage the risk.

477

478 In forest management, there are a variety of risks to consider, and a key question to ask is which
479 risks does the decision maker want to manage (i.e. to ask the question “Risk of ‘what?’”). The
480 first two examples we examined focused on only one kind of risk: the risk associated with the
481 NPV. Other decision problems may focus on different risks, such as the risk of achieving a
482 specific target for periodic income (Eyvindson and Kangas 2014), the risk of low biodiversity or
483 ecosystem provisioning occurrences, and the risk of planting a specific tree species (Hartikainen
484 et al. 2016). The other question to ask is “How will this risk be managed?”. Managing risk
485 requires a choice and can involve a trade-off with other aspects of interest. For instance, risk can
486 be mitigated through the improvement of the quality of information, but often this improvement
487 comes at a specific cost. Alternatively, as Robinson et al. (2016) suggest the variance of
488 harvested volume can be minimized by harvesting stands which have higher predicted accuracy.
489 However, this approach requires an explicit cost of increased harvesting area (Eyvindson and
490 Kangas 2017). Thus for this example, the trade-off is between increased harvesting accuracy and
491 increased harvested area.

492

493 Another important aspect to consideration is how the estimates of uncertainty have been
494 evaluated. For statistically based uncertainty estimates (i.e. inventory estimates, growth errors or
495 price uncertainty) risk management efforts can be easily justifiable. These estimates will be
496 unbiased and can be relatively easy to incorporate into the optimization process. For uncertainty
497 estimates based on expert judgment (Oppenheimer et al. 2016), a more careful approach to risk
498 management is needed. This is linked to the concept of deep uncertainty, where the actual
499 uncertainty is unknown, and the estimates for this uncertainty is poor. We still advocate the use
500 of this ‘poorer’ information, as it reflects the best information we currently have, and most likely
501 the expert judgement will not always be completely incorrect.

502

503 **3.2 Adaptive planning**

504

505 Managing risk can be seen through the lens of adaptive management, decision makers should
506 change the plan as the situation requires (Savage 2010, Yousefpour et al 2012). From a planning
507 perspective, there are multiple approaches for planning to conduct adaptive planning. For our use,
508 we propose three adaptive planning approaches. The simplest adaptive planning option is to
509 create a plan based on current information using a deterministic approach (i.e. a model using a
510 single scenario could reflect the average case, best or worst case) and re-plan as relevant new
511 information becomes available (labelled as 1 in Figure 1). The second approach of adaptive
512 planning is slightly more complicated which incorporates risk measures and the risk attitudes of
513 the decision maker and then to conduct a re-planning is done as new information becomes
514 available (labelled as 2 in Figure 1). The third approach pre-emptively suggests the optimal time
515 to collect new information as a means to manage risk, in stochastic programming literature this is

516 referred to as 2-stage and multi-staged problems (labelled as 3 in Figure 1). Depending on the
517 structure of the problem, the benefit of integrating risk management will vary. For each case, we
518 identify the potential benefits of managing risk through a simple scale: (a) high potential, (b)
519 moderate potential and (c) low potential. These potentials refer to the ability to impact change in
520 the objective value when risk is included in the management problem.

521

522 Selection of an approach to adaptive planning determines how risk can be integrated into the
523 problem. Very simply put, the more restrictive approaches to adaptive planning are less
524 computationally demanding and easier to formulate and comprehend. Thus, we are left with a
525 need to select the planning approach which meets the needs of the decision maker with the aim
526 of keeping the model as parsimonious as possible. To appropriately select a model for risk
527 management, the forest planner should consider the properties of the information, the context of
528 the management problem (what are the objectives and constraints of the problem) and the
529 availability and benefit of obtaining updated information.

530

531 In Figure 1, we propose a decision tree for selecting an appropriate approach to managing forests
532 under risk and uncertainty. Through a set of ordered questions, the planner is guided to
533 systematically think through the structure of the management problem, and a suggestion for
534 which approach to adaptive planning could be used. For two cases (5 and 9), all methods of
535 adaptive planning could be appropriate. For case 5, a deterministic approach may be suitable, if
536 the model requires a specific flow of timber for the worst case scenario. Alternatively, a two-
537 staged or multi-staged model may be suitable if continual monitoring of the forest resources will
538 be conducted to minimize the negative impacts caused by the restrictive specific flow of timber

539 constraint. As the two-staged and multi-staged problems are rather complex, the planner should
540 be able to clarify the benefits from its use. If the decision to collect new information will be
541 based on other factors (new inventory conducted by governmental agency), there is little benefit
542 from including the added complexity.

543

544 **4. Conclusions**

545 Management of risk should be done comprehensively using a parsimonious model which reflects
546 the requirements of the decision maker. As a parsimonious model, the problem formulation
547 should include only those key uncertainties which impact the problem at hand. For any specific
548 problem, various sources of uncertainty may hold relevance. By including only the key
549 uncertainties, the results should remain understandable to both the decision makers and forest
550 managers. When developing a plan, the decision makers should be made aware that risk
551 management should not focus on the complete elimination of risk. Nor should the plan present a
552 complete enumeration of all potential decisions for each possible resolution of the uncertainty.

553

554 We suggest this philosophy towards risk management for two key reasons. From the planning
555 professional's perspective, modelling risk and uncertainty in a comprehensive fashion is difficult
556 to accomplish conceptually. In addition, finding a solution to these problems may not be
557 tractable due to the technical challenge of finding solutions. From the user's perspective, a
558 detailed plan with many sources of uncertainty may hold only moderate improvement in value,
559 or maybe of less value due to the conceptual challenges of interpreting the plan. To promote
560 usability, the planned decisions which include risk management should be as easy to understand
561 as deterministic plans currently produced. Additional valuable information based on the risk

562 preferences of the decision maker could be added to the plan, such as when to conduct a new
563 inventory.

564

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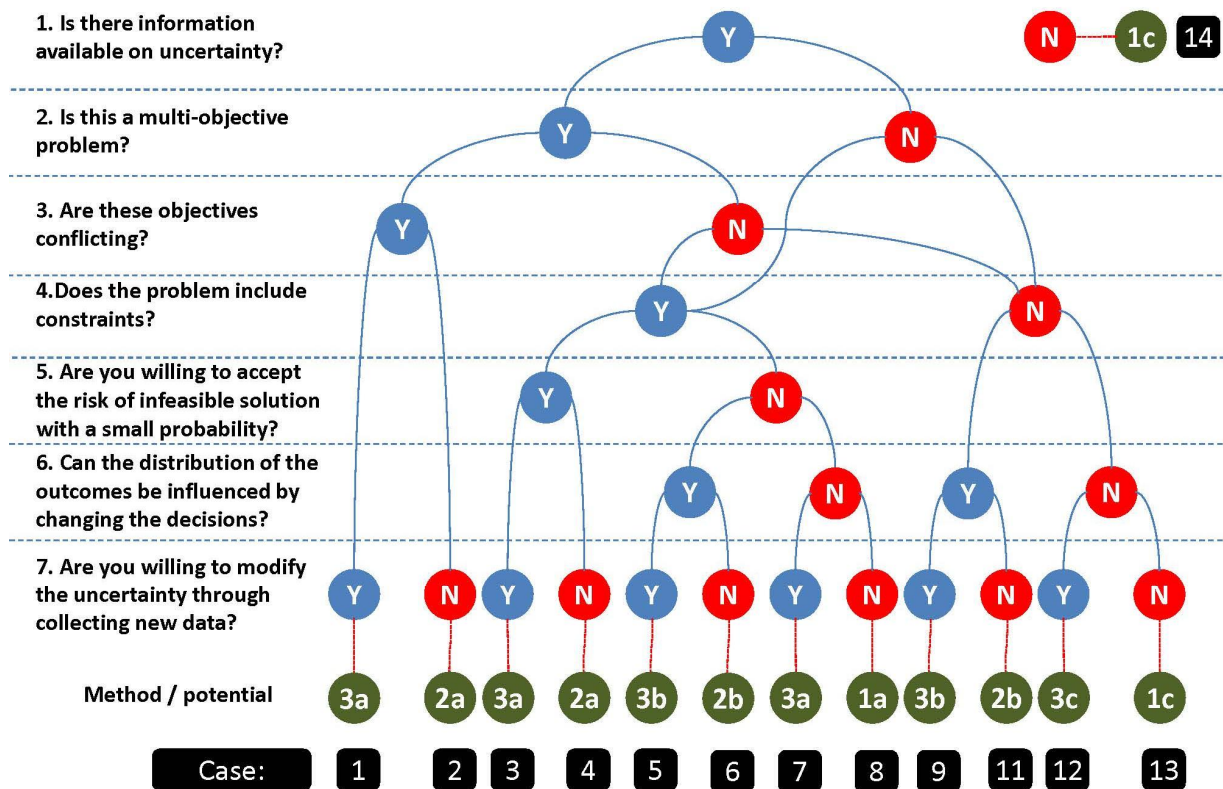
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695



696

697 Figure 1. Decision tree for selecting a modelling framework for forest management planning.

698 Choices for how to incorporate risk management is based on the the availability and
 699 updatability of the uncertainty information (questions 1 and 7) and the structure of the
 700 model (questions 2-6). Three alternatives for adaptive planning are highlighted, (1)
 701 deterministic planning and re-plan as new information becomes available, (2) manage
 702 risk (through risk measures, or other proxies) and re-plan as new information becomes
 703 available, (3) pre-emptively determine the optimal time to collect new information as a
 704 means to improve the management of risk (through risk measures or other proxies). The
 705 potential for risk management is highlighted by the letter after the method, (a) there is a

706 high potential for risk management, (b) a moderate potential for risk management and (c)

707 a low potential for risk management.

708