

# Review. Assessing uncertainty and risk in forest planning and decision support systems: review of classical methods and introduction of innovative approaches

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## Abstract

*Aim:* Since forest planning is characterized by long time horizon and it typically involves large areas of land and numerous stakeholders, uncertainty and risk should play an important role when developing forest management plans. The aim of this study is to review different methods to deal with risk and uncertainty in forest planning, listing problems that forest managers may face during the preparation of management plans and trying to give recommendations in regard to the application of each method according to the problem case. The inclusion of risk and uncertainty in decision support systems is also analyzed.

*Area:* It covers the temporal and spatial scale of forest planning, the spatial context, the participation process, the objectives dimensions and the good and services addressed.

*Material and methods:* Several hundreds of articles dealing with uncertainty and risk were identified regarding different forestry-related topics and approaches. From them, around 170 articles were further reviewed, categorized and evaluated.

*Main results:* The study presents a thorough review and classification of methods and approaches to consider risk and uncertainty in forest planning. Moreover, new approaches are introduced, showing the opportunities that their application presents in forest planning.

*Research highlights:* The study can aid forest managers in the decision making process when designing a forest management plan considering risk and uncertainty.

**Key words:** operations research; optimal alternative; stochastic risk; endogenous risk; stand level; forest level.

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## Introduction

Forest planning deals with different types of forest management decisions at various scales. One very typical characteristic of forest planning is the long-term nature of the decision outcomes. This can cause serious difficulties since decision making with long time horizon involves various sources of uncertainty. Uncertainty can be considered as lack of information. This means that the decisions have to be made without exact information about the parameters affecting them,

or about their outcomes. Definitions for the term uncertainty are many, although a general definition is still lacking (Kangas and Kangas, 2004).

Uncertainty has also been classified in many ways. One option is to divide uncertainty into aleatoric (or statistical) and epistemic (or systematic) uncertainty. Aleatoric uncertainty is something that we can describe, for example, with a statistical measure, such as a distribution, but it cannot be reduced with additional information. Epistemic uncertainty, on the other hand, can be reduced with additional measurements. These two classes have also been called variability and ignorance (Ferson and Ginzburg, 1996). Uncertainty may also be classified into metrical (measurement uncer-

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tainty), structural (complexity of systems), temporal (temporal variability) and translational uncertainty (in explaining uncertain results) as in Rowe (1994). Walker *et al.* (2003) defined uncertainty as a continuum between absolute determinism and total ignorance, with the following classification: determinism, statistical uncertainty, scenario uncertainty, recognised ignorance and total ignorance.

Risk can be defined as the known probability of some, often unwanted, occurrence (Willet, 1901). In the framework of forest planning, risk has been defined as the expected loss due to a particular hazard for a given area and reference period (Gadow, 2000). An expected loss may be calculated as the product of the damage and its probability. Risk is therefore characterized by presenting probabilities of occurrence that are known. However, as these probabilities are often set in a subjective way, it becomes difficult to differentiate between risk and uncertainty (Moss and Schneider, 2000). Uncertainty can be related to the existence of a risk, or to the lack of knowledge, or even to the degree of realization of one event (for instance regeneration) that does not need to mean risk. Even in the cases where the difference between uncertainty and risk might not be clear enough, it is advisable to integrate them into the planning process.

Within this framework, the most prominent sources of risk and uncertainty affecting decision making are:

- Uncertainty due to forest inventory errors; the present state and current properties of the forests are not known exactly.

- Uncertainty due to growth prediction errors; the future growth of forests cannot be predicted exactly since the growth models include errors and forest growth varies naturally in a stochastic fashion.

- Uncertainty due to the performance of timber markets; the future prices of timber assortment cannot be known perfectly, yet the timber prices have a considerable effect on the economic profits

- Uncertainty in the preferences of the decision maker (DM)—decision makers cannot state their exact preferences and priorities— or even to the evolution of the preferences of the forest owner, which may not be constant all over the planning period.

- Risks due to natural hazards, including: snow- and wind damages, forest fires, pathogens, insects, drought and flooding

As it has been previously mentioned, the time-horizon in forest planning decisions is typically quite long, “long” referring commonly to tens and even up to hundreds of years (Annex 1), and therefore the deci-

sions have long-term consequences. Bad decisions can have undesired effects that span over long periods of time. Decisions are based on predicted developments and outcomes, which are in general the more uncertain the longer the time-horizon is. When making decisions under uncertainty, the decision maker may end up with decisions that are not optimal, or not even feasible. Although many times these sources of risk and uncertainty have been ignored, they should be integrated into the planning process. By ignoring these sources of uncertainty and risk, the forest manager will achieve suboptimal solutions, in the best case, if not bad alternatives (Pukkala, 1998; Thorsen and Helles, 1998). In the best case scenario, *i.e.* no taking uncertainties into consideration without achieving worse alternatives, it is not known beforehand what the outcome will be (Pukkala, 1998). Non optimal decisions can lead to losses in the utility of the decision maker, for instance losses in the economic return (Burkhart *et al.*, 1978; Hamilton, 1978; Pukkala, 1998; Eid, 2000; Duvemo and Lämås, 2006). Understanding and considering the various uncertainties can help to avoid the non-optimal and infeasible decision.

Forest planning decision making is often aided by Forest Planning Systems (FPS), which are typically forestry-specific model-based decision support systems (DSS), and, therefore it would be advisable to consider also uncertainties in the FPS. Reckhow (1994) noted that “recognition of uncertainty does not prevent decision making, but provides an additional criterion for selecting between alternatives and deciding what, if any, additional information is needed. In this context, uncertainty assessment adds value to the DSS result”. Mowrer (2000) also motivated the recognition of the various uncertainties by stating that “including all the sources of uncertainty in all decision analyses might not be a feasible task. However, it is wise to be aware of as many of them as possible”. Moreover, Mowrer (2000) also pointed out that regarding the various capabilities of DSSs, uncertainty assessment is the most poorly understood and implemented. As an example, Lahdelma *et al.* (1998) stated that according to their experiences “the decision makers in public political decision situations prefer methods which do not require them to express their preferences explicitly but rather describe the potential actions and their consequences in an appropriate form, in order to allow the final decision to be made by themselves”. In this kind of situation there is clearly a need for tools to take the decision maker’s uncertainty, into account.

Pukkala (1998) stated that all results and outputs from forest planning calculations and predictions of forest development should be accompanied by an estimate of its reliability or its uncertainty. In this way the uncertainty associated with the outputs could be taken into account in the decision making. Ascough II *et al.* (2008) pointed out that “the type or quality of the uncertainty assessment, and the scientific tools employed in that assessment, must be decided pragmatically as part of the infrastructure (including cost) and system dynamics of the decision-making process”. This requires that the aspect of uncertainty is considered already when designing the forest planning DSS.

Although there are several sources of uncertainty and the importance of considering all of them in the decision making process has already been discussed, the present study is only focused on uncertainty sources related to forest planning and decision support systems. Recent studies have analyzed and reviewed the topic of modeling hazards and risks in order to integrate them in the planning process (Hanewinkel *et al.*, 2011) and the decision making techniques employed to assess risk and uncertainty due to climate change (Yousefpour *et al.*, 2012). Besides, the objective of this article is to review different methodologies and approaches that have been used in forest planning, as well as in different areas of knowledge, serving as a guide for forest managers, stakeholders and DSS developers to choose the most suitable method to account for risk and uncertainty in forest planning. Moreover, the inclusion of risk and uncertainty in decision support systems is considered and analyzed. In addition, this review presents innovative methodologies that may have been employed in other areas of knowledge but forestry.

## Material and methods

Firstly, several hundred (1935) of articles were identified in a search in Science Direct using the following keywords: forestry, planning, risk, uncertainty and optimization. From them, 170 articles were further reviewed, categorized and evaluated. The categories included information regarding the sources of uncertainty analyzed in the articles, and the dimensions of the problems addressed (the dimensions analyzed in this article are found in the Annex 1). The dimensions include the temporal scale, the spatial context, spatial scale, the participation process, the objectives dimen-

sions and the goods and services addressed. Note that readers are assumed to have knowledge about the different techniques mentioned in this review. A comprehensible description of each technique is therefore out of the scope of this article (see Hillier and Liebermann, 1990; Taha, 1992; Burke and Kendall, 2005, for references).

## What sources of uncertainty should be considered in forest planning and FPS?

As Mowrer (2000) stated, it is not feasible to consider all uncertainties in a DSS or in forest planning either. One way of selecting the uncertainties that need to be considered is to study the negative effects that occur when uncertainties are ignored (this is referred in this article as inoptimality losses).

The economic inoptimality losses due to forest inventory errors in harvest scheduling problems have been examined using cost plus loss analysis. The average inoptimality losses have been ranging from under 1% of stand-level Net Present Value (NPV) to around 6-7% (see for example Eid, 2000; Holmström *et al.*, 2003; Eid *et al.*, 2004; Holopainen and Talvitie, 2006; Duvemo and Lämäs, 2006; Borders *et al.*, 2008; Duvemo, 2009; Islam *et al.*, 2009; Mäkinen 2010).

Inoptimality losses due to growth prediction errors have been so far studied using cost-plus-loss analysis only by Pietilä *et al.* (2010) and by Mäkinen *et al.* (2012). Both studies concluded that the inoptimality losses varied between 3.3% and 11.6% of the stand-level NPV and depended on the inventory interval. This suggests that the effect of growth prediction errors in harvest scheduling planning problems is at least as significant as the effect of forest inventory errors. Similar results were observed by Mäkinen (2010) when comparing the effects of various uncertainties in stand-level NPV estimates, although not in inoptimality losses.

Stochastic variation in timber prices can also affect the economic profits of forest management considerably (*e.g.* Taylor and Fortson, 1992; Leskinen and Kangas, 2001). Holopainen *et al.* (2010) concluded that the effect of stochastic timber prices on stand-level NPV predictions was considerably less than the effects of inventory and growth model errors.

Natural hazards, such as high winds and forest fires cause damages which in turn lead to economic losses. Especially forest fires can also have other drastic effects than just damaged forests; forest fires can in-

flict expensive damage to buildings and infrastructure and even cause human casualties. Forest fire risk has been included in forest planning in several ways (e.g. González *et al.*, 2005; González-Olabarría *et al.*, 2008; Hyytiäinen and Haight, 2010; García-Gonzalo *et al.*, 2011a; Ferreira *et al.*, 2011, 2012), and in fact forest fire risk is one of the few examples where uncertainty and risk is considered in forestry DSSs (Kaloudis *et al.*, 2005; Bonazountas *et al.*, 2007). In Europe during 1950-2000, wind storms were responsible for 53% and forest fires for 16% of forest damages (Schelhaas *et al.*, 2003). In North-America, the economic effects of wind damages have been studied by Peterson (2000). Wind damages and forest management practices under the risk of wind damage have been studied, for example, by Lohmander (2000), Zeng *et al.* (2007) and Forssell (2009).

Another aspect one should consider when choosing the uncertainties to account for in forest planning and in the development of a FPS, is the available information about the nature of uncertainty. For instance, forest inventory errors associated with the various inventory methods have been studied extensively, and thus data availability is quite good [for compartment field inventory, see Poso (1983), Laasasenaho and Päivinen (1986), Kangas *et al.* (2004), and for Airborne Laser Scanning, see Naesset (2004), Kaartinen and Hyypää (2008), Packalen (2009)]. On the other hand, data on forest growth model errors may not be that readily available and collecting such data, including repeated measurements from permanent sample plots, can be very expensive. Information on past timber prices should be easy to obtain for different areas and timber assortments around the world. Data about natural hazards can also be difficult, or at least expensive, to obtain. It is important to note that exact information regarding the uncertainties is not necessary required, as subjective expert estimates about the uncertainties can be used instead.

The significance of various uncertainties is also affected by the type of the decision problem and the spatial and temporal scales. These should also be considered when deciding which of the uncertainties are accounted for in the decision making process as they may differ depending on the decision problem and the spatio-temporal scale. For example, errors in growth predictions may be important in tactical and strategic forest planning but may be even ignored in operational forest planning. Uncertainties can also have joint effects and decreasing the effect of some uncertainty

does not necessarily decrease the overall uncertainty notably.

Walker *et al.* (2003) proposed a general framework for describing the various uncertainties in model-based DSSs, called uncertainty matrix. The uncertainty in the matrix is defined as a three dimensional concept defined by: the location in the analysis, the level of uncertainty, and the nature of the uncertainty. These types of tools would be very helpful in describing and understanding the various uncertainties in complex systems and also for communicating the uncertainties between groups of experts.

Although it is generally agreed that considering uncertainties in DSSs, and also in forestry context, is of importance, the actual implementations of uncertainty considerations in FPSs are few. The number of alternative approaches and methods for considering uncertainty is considerable, so the lack of implementations must lie somewhere else.

### General uncertainty and risk consideration methods

Before analysing the methods for integrating risk and uncertainty in forest planning, it is also interesting to introduce different uncertainty theories (Kangas and Kangas, 2004). These uncertainty theories have been used in decision analysis and the adoption of one or other theory depends on the characteristics of the uncertainty analyzed. The main approaches are the probabilistic framework, Bayesian probability theory, the evidence theory, fuzzy set theory and possibility theory. The traditional approach for analysing uncertainty is the classical probability theory, and especially Kolmogorov probability theory (Williams, 1991). In the probabilistic framework the probabilities are presented by means of probability distributions, which may be continuous or discrete, and uncertainty is considered as random variability. In contrast the Bayesian theory (Carlin and Louis, 2000) deals with subjective probabilities that describe prior beliefs about the values of the parameters. Evidence theory is similar to this latter approach, the main difference being that the subjective beliefs are needed here to obey the probability rules. Fuzzy set theory (Zimmermann, 1985) accounts for the uncertainty derived from the vagueness in defining the criteria, preferences, etc.

Among the ways to deal with risk and uncertainty, one preliminary option is to prioritize the use of adap-

tive planning (McLain and Lee, 1996; Jacobson and Thorsen, 2003; Zhou *et al.*, 2008; Leskinen *et al.*, 2009) instead of anticipative of fixed prescriptions. In adaptive planning, the state of the system is observed intermittently and decisions are made on the basis of these observations. For example, the timing of harvest and the post-harvest state depend on the stand and market conditions at the time when the decision is made. Examples of adaptive studies are the inclusion of stochastic stumpage prices, stochastic stand dynamics (Kao, 1984) or both (Kaya and Buongiorno, 1987; Lohmander, 1987) and stochastic fire (Ferreira *et al.*, 2011, 2012). Anticipatory models are used for deriving optimal decisions for the whole planning period in advance. The solution takes into account the uncertainties over time. This method is preferable to adaptive ones when the state of the system is not observable after a decision is made, or when meaningful feedback rules are difficult to identify. Kao (1982) is an example of anticipatory model using stochastic dynamic programming when stand volume growth is stochastic. Fixed policies (*i.e.* anticipatory models) have been based on silvicultural experience supplemented by measurements or on optimization models. When optimization models are used they are mostly of a deterministic type, but stochastic optimization methods have also been applied to obtain fixed policies (*e.g.* González *et al.*, 2005; Liang *et al.*, 2006; González-Olabarría *et al.*, 2008).

In the present study methods that have included risk and uncertainty are grouped in different categories depending on the characteristics of the planning problem addressed, *e.g.* the spatial scale, the temporal scale and the decision makers involved in the planning process. At the spatial scale three different levels are identified in forest planning, namely stand level, forest/landscape level and regional level. The stand level is focused only on the dynamics of a single stand and its management policies. At the forest/landscape level the complexity grows and more objectives and constraints have to be accounted for. The highest hierarchical level is the regional level. At this level forest planning must focus, not only in forest issues but also on topics such as social policies, industry interests or sustainability. The next consideration is on regard to the temporal scale and also three different categories are analyzed: strategic, tactical and operational planning. Depending on the decision makers involved, decisions can be individual or with more than one decision maker (*e.g.* collegial). Different methodologies are studied atten-

ding also to the nature of the problem (*i.e.* which are the objectives pursued with the planning process as well as on the decision makers involved).

Based on these general categories, some other differences can be analysed, *i.e.* the difference between stochastic and deterministic models and the way to use them (Boychuck and Martell, 1996; Hellander, 2009). According to Beaudoin *et al.* (2007) a fundamental property of deterministic models is that all required data are supposed to be known with certainty, whereas in the case of stochastic models data is commonly expressed by means of probability distributions. Moreover, in the case of catastrophic events an interesting differentiation is the one between endogenous and exogenous risk and the advantages of considering one over the other (Thorsen and Helles, 1998; González *et al.*, 2005; González-Olabarría *et al.*, 2008; Pasalodos-Tato and Pukkala, 2008; Pasalodos-Tato *et al.*, 2009; García-Gonzalo *et al.*, 2011a; Ferreira *et al.* 2012). Endogenous risks are those which are related to the state of the stand and therefore may be influenced by management, for instance the probability of occurrence of a fire or the post-fire mortality (González *et al.*, 2005; Pasalodos-Tato *et al.*, 2010; García-Gonzalo *et al.*, 2011b).

## Classification of methods to deal with risk and uncertainty

### Stand level

The stand is the first meaningful unit in forest planning (Valsta, 1993) and at the stand level forest planning aims to solve the possible problems related to the management of a single stand. Although the stand level seems to be a too simplistic approach in forest planning, it is very useful, not only to support forest planning at the landscape level but also to help small forest owners to develop the management of their stands optimally (Pasalodos-Tato, 2010). Forest planning at the stand level mostly involves the resolution of problems in a long-term horizon, *i.e.* policies for the optimal management of individual stands and finding optimal thinning schedules and rotation lengths. In a time-scale classification it corresponds to strategic forest planning. Several sources of uncertainty can take place, *e.g.* uncertainty related to the expected growth of the trees, uncertainty regarding the fluctuations in market conditions and timber prices, the occurrence of a catastro-

**Table 1.** Different methods used to integrate risk and uncertainty at stand level

Strategic/tactical level		
<b>Optimize harvest scheduling (rotation length, thinning regimes)</b>		
<i>Nonlinear programming</i>		
Simulation (deterministic)	Catastrophic events	Thorsen and Helles (1998), Pasalodos-Tato and Pukkala (2008), Pasalodos-Tato <i>et al.</i> (2009, 2010)
Simulation (stochastic)	Catastrophic events	Pukkala (1998) Moykkynen <i>et al.</i> (2000), González <i>et al.</i> (2005), González-Olabarría <i>et al.</i> (2008), Hyytiainen and Haight (2010)
Sensitivity analysis (scenario analysis, stochastic optimization)	Uncertainty in yearly growth and catastrophic events	Valsta (1992), Pukkala and Miina (1997)
	Stochastic timber prices	Pukkala and Miina (1997)
	Attitude towards risk	Pukkala and Kangas (1996)
	Preferences of the DM	Pukkala and Miina (1997)
<i>Dynamic programming</i>		
Deterministic approach	Catastrophic events	Martell (1980)
Stochastic dynamic programming (scenario analysis technique, stochastic simulation)	Catastrophic events	Kao (1982)
	Uncertainty in growth	Kao (1984); Kooten <i>et al.</i> (1992)
	Preferences of the DM	Couture and Reynaud (2008)
	Stochastic prices	Lohmander (2007)
Markov chains (scenario analysis technique, stochastic simulation)	Uncertainty in growth	Kaya and Buongiorno (1987), Buongiorno (2001)
	Uncertainty in growth and prices	Lin and Buongiorno (1998), Lohmander (2000), Insley and Rollins (2005), Rollin <i>et al.</i> (2005), Zhou <i>et al.</i> (2008)

phic event, changes in the preferences of the forest owners regarding the objectives aimed with the planning and even variations in social preferences that might change the trends in land use and therefore affect the stand management. Several methods have been used to integrate risk and uncertainty at this level (Table 1).

The most widely employed methods to optimize stand level management in strategic planning comprise non-linear programming and dynamic programming. When dealing with risk and uncertainty, the applied methods are usually stochastic, although deterministic methodologies have also been employed by weighting every expected outcome by its probability of occurrence (Reed, 1984; Thorsen and Helles, 1998; Englin *et al.*, 2000; Pasalodos-Tato and Pukkala, 2008; Pasalodos-Tato *et al.*, 2009). One of the most common methodologies employed to integrate uncertainty and risk is the scenario analysis technique (Rockafellar and Wets, 1987; Valsta, 1992). This approach consists in the creation of different scenarios. A scenario is defined as one

realization over time of the stochastic processes (Valsta, 1992) and may be directly integrated in the objective function. By assigning probabilities (risks) to the scenarios, expected values could be used in the objective function. This method has been employed by many authors to integrate classical sources of uncertainty and risk: uncertainty in yearly growth and catastrophes (Valsta, 1992; Pukkala and Miina, 1997), in the success or occurrence of a certain event, *e.g.* the regeneration of a stand (Miina and Heinonen, 2008), stochastic behavior of timber prices (Pukkala and Miina, 1997), attitude towards risk (Pukkala and Kangas, 1996) and preferences of the decision maker (Pukkala and Miina, 1997).

One variation of the scenario technique is the stochastic simulation. This method is rather flexible and can be adapted to different optimization techniques. The key point of the methodology is to define the problem as a stochastic simulation model (Lohmander, 2007). Some authors have implemented the simu-

lation by means of random number generators (González *et al.*, 2005), probability distributions (Pukkala, 1998) or using also Monte Carlo techniques (Kaya and Bongiorno, 1987). The method has been widely employed to integrate risk (Möykkynen *et al.*, 2000; González *et al.*, 2005; González-Olabarría *et al.*, 2008; Hyytiäinen and Haigh, 2010) and uncertainty (Kaya and Bongiorno, 1987; Pukkala and Miina, 1997) in forest planning.

Optimization techniques that have been commonly applied with scenario analysis technique or stochastic simulation are non-linear programming and direct search methods. A classic direct search method widely used has been the one developed by Hooke and Jeeves (1961). Recently new direct search methods called population based methods have been tested (Pukkala, 2009).

Dynamic programming techniques have also been employed in some of the first studies related to risk of fire (Martell, 1980) in a deterministic way. In this study stochastic dynamic programming was used to deal with risk when finding optimal management alternatives to optimize stocking level and rotation length: Kao (1982) presented a study dealing with uncertainty in growth predictions due to fire occurrence or storms where they used fixed probabilities of occurrence. This model would be applicable for these risk factors if the probabilities of their occurrence and the associated growth are known. This method has also been used under growth uncertainty (Kao, 1984; Kooten *et al.*, 1992) and to set optimal fire management strategies (McCarthy *et al.*, 2001). This technique has also been used to find optimal harvest timing when timber, carbon benefits and the forest owner's preferences are considered (Couture and Reynaud, 2008). In the case of stochastic prices this method was also successfully applied [see Lohmander (2007) for references]. Recently, Ferreira *et al.* (2011, 2012) have used stochastic dynamic programming to determine the optimal stand policy (*i.e.* the fuel treatment, thinning schedules and rotation length) under risk of wildfire. They considered probability of wildfire and potential damage as endogenous (*i.e.* dependent on the state of the stand).

Markov decision process is another technique commonly employed to deal with risk and uncertainty in stand growth and prices (Kaya and Bongiorno, 1987; Lin and Bongiorno, 1998; Lohmander, 2000; Bongiorno, 2001; Insley and Rollins, 2005; Rollin *et al.*, 2005; Zhou *et al.*, 2008).

The next temporal scale the tactical level, which drives medium term decisions. The tactical level is a brid-

ge between strategic level and operational level. Tactical planning at stand level usually deals with thinning and/or final cutting scheduling problems. The forest manager needs to decide which area of the stand will be clear cut or thinned and when. The uncertainty involved at the tactical level is usually related to stochastic prices as well as on stochastic growth. Risk of a catastrophic event is also important. The methods employed to deal with risk and uncertainty at the tactical level are similar to the ones employed at the strategic level.

At the operational scale (short-term decisions) stand level forest planning has to deal with issues such as choosing the harvest units that need to be cut in short periods (*e.g.* a week), the machinery that might be used, to schedule the transportation and the way the trees have to be bucked (Epstein *et al.*, 2007). Although stand level planning at both the tactical and the strategic level do not include spatial restrictions or area assignment, at the operational level this type of constraints may be needed and therefore the methodology employed varies from the previously described ones. In cases such as the selection of the areas to be cut in a specific periods, linear programming techniques (LP), even at the stand level, are applied. Nevertheless this issue is much more important at the forest level and, therefore, it will be explained with more detail when dealing with landscape level planning problems. Another issue is the location of the machinery in the forest; these problems may be solved by combining GIS with heuristic search. To set the tree bucking model is another typical problem at this level, generally solved with LP although fuzzy logic, dynamic programming and heuristics have also been employed as resolution methods (Sessions, 1988; Sessions *et al.*, 1989; Kivinen and Uusitalo, 2002; Kivinen, 2004). Uncertainty at this level would be related to climatic conditions or to variation in timber prices or in transportation costs, for instance. The way to deal with these sources of uncertainty is the same as when integrating stochasticity in LP, heuristics and dynamic programming, although no examples have been found. This may be due to the fact that the time horizon considered at the operational level is so short that the potential sources uncertainty or risk involved are not considered to be important. The first two techniques (LP and heuristics) will be explained in more detail when assessing the forest level problem.

At the stand level usually the forest owner is the only decision makers involved in the process. Nonetheless, an important source of uncertainty is the uncertainty

regarding the preferences of the decision maker and his attitude towards risk. Usually, the way to account for the uncertainty related to the decision makers' preferences has been the scenario technique (Pukkala and Kangas, 1993; Pukkala, 1998). There are also other types of uncertainties, for instance, those related to the capability of the DM to express his/her preferences (fuzzy programming). Various approaches have been developed for decision support in situations where multiple utilities need to be considered, generally called Multi Criteria Decision Making (MCDM). So far most of the applied MCDM methods are based on Multi Attribute Utility Theory (MAUT). Many of the MCDM methods can handle uncertainties to some extent and many of them have been applied in forest planning context. One of the widely applied approaches is the Analytic Hierarchy Process AHP (Saaty, 1980; Leskinen and Kangas, 1998). Another MCDM method capable of handling uncertainties is Stochastic Multiobjective Acceptability Analysis SMAA (Lahdelma *et al.*, 1998). Outranking methods, such as ELECTRE and PROMETHEE are MCDM method in which the uncertainties of the decision variables can be accounted for using fuzzy relations (Kangas *et al.*, 2001). For instance, PROMETHEE has been employed recently to evaluate the impact of different hazards on different forest management alternatives in several European regions (Jactel *et al.*, 2012).

#### *Forest/landscape level*

At the forest level the main objective is to find the best combination of stand treatment schedules in order to achieve a general objective for the whole forest rather than maximizing/minimizing an objective function for each of the stands (Heinonen, 2007). Forest planning usually includes landscape goals, such as patterns of old forest patches or cutting areas quantified by landscape metrics, which make problems difficult to solve (Heinonen, 2007). Therefore forest planning may comprise non-spatial and spatial problems. Non-spatial means that a treatment of a stand has no effect on the treatment of other stands due to their location. Examples of this kind of problems are the requirement of an even-flow of timber, minimum or maximum harvesting levels, maximum total regeneration area, minimum growing stock value and maximization of carbon stocks. These are the typical goals at the strategic level. Non-spatial problems can be efficiently solved using

LP models (Table 2). A problem with LP is that it does not guarantee the integrity of the stands, *i.e.* the optimal solution will include partially treated stands. If the integrity of each stand must be preserved, mixed integer programming (MIP) can be used instead of linear programming. LP and MIP are deterministic methods, but there are several ways to include uncertainty in LP and MIP: (i) expected value approach or mean value process is a simple and deterministic method; (ii) scenario analysis presents an improvement over the latter approach since each scenario problem is treated as a linear programming model; (iii) sensitivity analysis; (iv) stochastic programming, (stochastic linear programming and stochastic integer programming). The mean value process (Reed and Errico, 1986; Gunn and Rai, 1987) has been employed by Reed and Errico (1986) to manage timber supply when fire occurs. In this article the expected burned area was subtracted from each age class in each time period and added to the youngest age class in the following period and solved the mean-value problem. Scenario analysis, or simulation, in which alternative scenarios are evaluated, was employed by Klenner *et al.* (2000) and Gadow (2000). Peter and Nelson (2005) used this methodology to estimate harvest schedules and profitability under the risk of fire disturbance.

There are also genuinely stochastic programming techniques (see Sahinidis (2004) for a brief explanation of the techniques): (i) programming with recourse, that includes techniques such as stochastic integer programming (as well as stochastic linear programming), stochastic non-linear programming and robust stochastic programming; (ii) probabilistic or chance-constrained programming; (iii) fuzzy mathematical programming that includes flexible programming and possibilistic programming.

Programming with recourse is a modeling technique to explicitly consider uncertainty in optimization models, and it also gives the opportunity to adjust the decisions to the information that is received after a random event or scenario has occurred, which is referred as "recourse". Boychuck and Martell (1996) introduced the concept of scenarios in a forest-level analysis of forest fires with the implementation of stochastic programming with fixed recourse. To account for the uncertainty in the modeling process, stochastic programming integrates it through scenarios of random events with a given probability of occurrence. This technique was employed to assess uncertainty in timber yield (Hoganson and Rose, 1987; Eriksson, 2006) and

**Table 2.** Different methods used to integrate risk and uncertainty at forest planning level

<b>NON SPATIAL</b>		
<b>Maximization of sustained harvest volume flow, harvest schedule, the maintenance of biodiversity values</b>		
<b>STRATEGIC</b>		
<b>LP, MIP</b>		
Expected value approach	Catastrophic events	Reed and Errico (1986), Gunn and Rai (1987)
Scenario analysis	Catastrophic events	Klenner <i>et al.</i> (2000), Gadow (2000), Peter and Nelson (2005)
Sensitivity analysis		
Stochastic LP		
<b>Stochastic programming</b>		
Programming with recourse	Catastrophic event	Boychuck and Martell (1996) Gassmann (1989)
	Uncertainty in timber yield	Hoganson and Rose (1987) and Eriksson (2006)
Probabilistic or chance-constrained programming	Uncertainty in timber yield	Pickens <i>et al.</i> (1991), Weintraub and Vera (1991), Weintraub and Abramovich (1995), Hof <i>et al.</i> (1996)
	Uncertainty on production requirements	Hof and Pickens (1991)
	Uncertainty in timber demand	Palma and Nelson (2009)
Fuzzy mathematical programming	Uncertainty in timber yield	Pickens and Hof (1991) and Bare and Mendoza (1992)
	Vague objectives and constraints	Mendoza and Sprouse (1989), Pickens and Hof (1991), Bare and Mendoza (1992), Mendoza <i>et al.</i> (1993), Teclé <i>et al.</i> (1994), Hof <i>et al.</i> (1995), Ellis <i>et al.</i> (1997)
<b>SPATIAL</b>		
<b>TACTICAL</b>		
<b>Heuristic</b>		
Scenario analysis technique	Catastrophic event	Meilby <i>et al.</i> (2001)
Scenarios of climate change	Uncertainty in climatic conditions	García-Gonzalo <i>et al.</i> (2008)
Risk as an objective variable	Risk of wind-throw minimization (and maximization)	Zeng <i>et al.</i> (2007)
	Effect of minimizing mean risk on the forest management	Heinonen <i>et al.</i> (2009)
Wildfire simulator (FARSITE) and the heuristic great deluge algorithm	Uncertainty in fuel management	Kim <i>et al.</i> (2009)
HERO+	Scenario approach (to integrate risk in timber prices and in level of tree growth + Priority function (preferences and the attitude toward risk)	Pukkala and Kangas (1996)
<b>Markov chain processes</b>		
	Climate change	Spring <i>et al.</i> (2005)
	Reserve site selection	Sabbadin <i>et al.</i> (2007)
	Risk of forest fire and wind effects	García and Sabbadin (2001), Spring and Kennedy (2005), Forsell <i>et al.</i> (2011)
	Maintenance of wildlife	Spring <i>et al.</i> (2008)
<b>OPERATIONAL</b>		
<b>LP, IP and heuristics techniques + stochasticity</b>		
	Location of areas to be harvested, location of machinery	
	Transportation problems	

stochastic fire losses in sustainable timber supply (Gassmann, 1989; Boychuck and Martell, 1996). These two latter approaches are the same that were already explained for introducing stochasticity at the stand level when employing nonlinear techniques. Another way to integrate stochasticity in linear programming is by the post-optimal or sensitivity analysis. It was employed by Pickens and Dress (1988) to study the effect of stochastic technological coefficients in forest level timber management models.

Probabilistic or chance-constraint programming is a stochastic programming technique where constraints with at least one random coefficient are modeled as probabilistic statements and are required to hold a minimum probability. It is similar to stochastic programming in the sense that the probability distributions of uncertain coefficients are assumed to be known, but no recourse or correcting actions are explicitly assumed. This approach has been applied to deal with randomness in timber growth (Pickens *et al.*, 1991; Weintraub and Vera, 1991; Weintraub and Abramovich, 1995; Hof *et al.*, 1996) and when there is uncertainty on production requirements (Hof and Pickens, 1991). Robust optimization has also been employed in harvest scheduling problems when volume and demand are randomly uncertain (Palma and Nelson, 2009). It is a modeling methodology combined with computational tools to process optimization problems in which the data set is uncertain and is only known to belong to some uncertainty set (Ben-Tal and Nemirovski, 2002).

Related to the fuzzy set theory, that accounts for the uncertainty derived from the vagueness in defining the criteria, fuzzy linear and goal programming (GP) techniques have also been employed to deal with risk and uncertainty. Mendoza and Sprouse (1989) proposed a two-stage approach for forest planning and developed a fuzzy model for more flexible and robust generation of alternatives. In this case, uncertainty arose from imprecise coefficients. Hof *et al.* (1986), Pickens and Hof (1991) and Bare and Mendoza (1982) compared classical and fuzzy models for describing optimal harvest over time. They found that, by relaxing the constraint of non-declining harvest volume over time, the net present value could be significantly increased. Mendoza *et al.* (1993) developed a fuzzy multiple objective LP model for forest planning that accommodated uncertainty in the objective function by making coefficients interval-valued. Teclé *et al.* (1994) developed an interactive fuzzy multicriterion decision model in which the decision maker is allowed to search the frontier of

efficient solutions instead of being confronted with a uniquely preferred solution. Bare and Mendoza (1992) and Pickens and Hof (1991) focused only in timber yield. Ells *et al.* (1997) were the first ones in combining the existence of vague objectives and constraints, as Teclé *et al.* (1994) and Pickens and Hof (1991) did, and imprecise coefficients as in Mendoza and Sprouse (1989), Bare and Mendoza (1992), Hof *et al.* (1996) and Mendoza *et al.* (1993). Ells *et al.* (1997) also modeled imprecise coefficients as fuzzy numbers and their approach gave more importance to the effect of the various sources of uncertainty in land allocation.

Spatial optimization can be divided into two categories: spatial optimization and spatially explicit optimization. Spatial optimization refers to the methods that capture spatial relationships between different land areas (*e.g.* neighborhood relations of stands) in the process of maximizing or minimizing and objective function subject to resource constraints. This is different from spatial explicit optimization (Hof and Haight, 2007), which simply involves variables that are spatially defined and includes no spatial relationships. Spatial objectives require consideration of the relative locations of stand in optimization calculations. When spatial objectives are included in the optimization process we talk about endogenous planning. Spatial problems can be dispersing or connectivity problems (Öhman, 2001; Heinonen, 2007).

Spatial restrictions or objectives are typically considered at the tactical and operational levels. At the tactical forest level, the operations or the harvest volumes defined in the strategic stage need to be allocated in the terrain. These spatial restrictions have the form of adjacency constraints, habitat continuity, etc. For both the spatial optimization problems (*i.e.* considering adjacency constraints) and the spatial explicit optimization (*i.e.* choice variables that are spatially defined) the methodologies used have been: integer programming (IP), mixed integer programming (MIP) (Rebain and McDill, 2003), heuristics (Öhman and Eriksson, 1998; Öhman, 2000; Öhman and Eriksson, 2002; González-Olabarría and Pukkala, 2012) and dynamic programming (Borges *et al.*, 1999; Hoganson *et al.*, 2003; Hoganson *et al.*, 2005). When using these methodologies there are different ways to include uncertainty and risk.

One of the main difficulties in planning harvesting operations in tactical planning is the stochasticity of future timber sale prices. The problem is therefore a Stochastic Programming (SP) that problem (see Birge

and Louveaux (1997) for a specialised book on this subject). In spatial explicit optimization, Stochastic Integer Programming (SIP) approaches must be used. Recently, Alonso-Ayuso *et al.* (2012) presented a methodology to deal with uncertainty in prices and future wood demand in a tactical forest planning aiming at determining the optimal harvest and access road construction policy that will maximize expected net profit and satisfy the constraints. The paper presents a multi-stage stochastic integer programming model which is solved using a branch-and-fix coordination approach.

Heuristics have been employed in combination with other approaches to integrate different catastrophic risks. Pukkala and Kangas (1996) developed a method to integrate risk and attitude toward risk in forest planning at the tactical level combining scenario approach (to integrate risk in timber prices and in level of tree growth), a priority function (to compute the preferences and the attitude toward risk) and a heuristic optimization algorithm, HERO (Pukkala and Kangas, 1993), to solve the problem. Meilby *et al.* (2001) included risk of wind in the objective function by means of scenario technique and then used simulated annealing to find optimal rotation length without even-flow cutting targets. Zeng *et al.* (2007) included risk of wind-throw minimization (and maximization) considering maximum cutting areas. García-Gonzalo *et al.* (2008) included uncertainty in climatic conditions by means of scenarios of climate change and then used heuristics to find optimal management plans for each scenario and to analyze the effect of not adapting management plans to climate change. In this paper they used even-flow cutting constraints but did not include spatial constraints. Heinonen *et al.* (2009) also used risk of wind-throw as an objective variable in the optimization to analyze the effect of minimizing mean risk on the forest management. Kim *et al.* (2009) employed a wildfire simulator (FARSITE) and the heuristic great deluge algorithm to optimize the pattern of fuel management. Another methodology to integrate risk and uncertainty at both strategic and tactical planning is Markov decision processes. As well as on the stand level case, Markov decision processes have also been employed to deal with uncertainty at the forest level (Sallnäs and Eriksson, 1989; Buongiorno, 2001). Forsell *et al.* (2011) included the risk of wind damage in long-term forestry management with the object of maximizing the expected net present value of the forest accounting for the spatial relationships of the stands. Other Markov decision process applications at forest

level have dealt with climate change (Spring *et al.*, 2005), reserve site selection (Sabbadin *et al.*, 2007), risk of forest fire (Spring and Kennedy, 2005; Garcia and Sabbadin, 2001), maintenance of wildlife (Spring *et al.*, 2008) and wind effects (Forsell *et al.*, 2011).

In regard to the operational planning at the forest level the main problems are location of areas to be harvested, location of machinery, transportation problems, etc. These problems could be solved by including stochasticity to LP, IP/MIP and heuristic techniques. Uncertainty related to this type of problem comes from the availability of wood and from variation in timber prices, as well as from weather and terrain conditions (*e.g.* impossibility to harvest in swampy areas). However previous literature has not been found on these topics.

### *Regional level*

At the top of the spatial-scale hierarchy is the regional level. At this level it is important not only to allocate the resources optimally to obtain the higher utility from the forest but also to develop certain policies involving as many stakeholders as possible in the process (Ananda and Herath, 2003): forest owners, industry sector, environmental groups, etc. As an example, an important issue at both the strategic and the tactical level are the implementation of timber supply chain. Timber supply chain is a good example of planning at the regional level. It contains the three temporal planning levels that we are dealing with. At the strategic level the main aim is to develop a good configuration of the road network for the region and to obtain sustainable harvest levels; at the tactical level the main issue is to decide the material flows (Beaudoin *et al.*, 2007), while at the operational level day to day decisions are involved.

At the tactical level, the multiproduct supply chain planning is an important issue (Mitra *et al.*, 2008). In this type of problems the most widely employed methodologies are stochastic programming, fuzzy mathematical programming and probabilistic programming or chance constraint programming. This latter approach is interesting because it focus on the system's ability to meet feasibility in an uncertain environment. The reliability is expressed as a minimum requirement on the probability of satisfying the constraints.

At the operational level the most common approaches have been the scenario/multi-period based approaches

and the probabilistic programming. It is interesting the approach of Ierapetritou *et al.* (1996) that combined stochastic programming with the value of perfect information. With this methodology the expected profit and future feasibility is balanced with DM's attitude towards risk.

Nevertheless, at the regional level the most widely analyzed uncertainties currently are the ones related to climate change. An extended example to deal with this type of uncertainty is the Integrated Assessment Approach (IA). This type of approach is characterized by having an added value compared to insight derived from disciplinary research. Global change has impulse the development of a new series of IA models; however, this topic is far beyond the scope of this study.

### Forestry DSSs involving uncertainty and risk considerations

Most of the forest planning or related DSSs that actually implement some kind of uncertainty considerations are tools for analyzing and managing different risks, such as forest fires, pests and other disturbances. Thus, they do not include decision aid components. The only example found is the SADfLOR v ecc 1.0 DSS developed in Portugal (García-Gonzalo *et al.* Submitted). This modular DSS includes a process-based growth and yield model capable of predicting growth under climate change conditions. Thus, multiple climate change scenarios may be taken into account. In addition, it includes a module that allows the generation of formulations in LP, MIP and GP. It also includes a meta-heuristic solution technique (*i.e.* Simulated Annealing). Examples of fire management DSSs these are Wildfire Destruction Danger Index WFDDI (Kaloudis *et al.*, 2005), which utilizes fuzzy set theory and DSS for managing forest fire casualties (Bonazountas *et al.*, 2007), where the uncertainty considerations are based on Monte Carlo simulation. Intensive and costly spruce budworm outbreaks in Eastern Canada led to the development of Spruce Budworm Decision Support System SBW DSS (MacLean *et al.*, 2001), which calculates the marginal timber yield utilities for protecting against budworm outbreaks. SBW DSS uses various scenarios with different outbreak and defoliation levels, which can be considered as uncertain and have to be decided by experts. LANDscape DIsturbance and Succession model (LANDIS) is a tool for assessing forest succession and disturbances at landscape-level

(Mladenoff, 2004; Scheller *et al.*, 2007). LANDIS includes a number of stochastic processes and can be used for uncertainty considerations by applying Monte Carlo simulation and scenario analysis (Xu *et al.*, 2005). Other forest planning DSSs with some type of uncertainty considerations might exist, but the amount relative to the total number of FPSs is very small.

### Innovative approaches

In this section recent approaches to deal with uncertainty and risk in forest planning are presented. Most of the methodologies presented here have been found in studies that assess uncertainty in different planning areas, *i.e.* chemical engineering, species conservation, etc. However, since uncertainty and risk are issues that require special attention in any type of planning, they can be adapted and used in forestry planning problems. Three different groups of innovative approaches have been considered depending on (i) the methodology employed to solve the planning problem, (ii) the nature of uncertainty and (iii) the way to characterize uncertainty.

The first group of recent approaches is related to those methodologies that have not been commonly employed in forest planning but show great potential to be implemented in the future. For instance, stand level problems when risk is involved, can be solved by new methodologies of population-based direct-search methods (Pukkala, 2009), *i.e.* are differential evolution (Storn and Price, 1997), particle swarm optimization (Kennedy and Everhart, 1995), evolution strategy (Beyer and Schwefel, 2002) and the Nelder and Mead method or polytope search and amoeba search (Nelder and Mead, 1965). As these methods only refer to the optimization technique, the way to integrate risk is the same as with other direct search methods. Another optimization technique that has not been commonly used at the stand level, are heuristics. Some heuristics, *i.e.* random ascent, simulated annealing, tabu search, threshold accepting, genetic algorithms, have great potential to be employed for solving stand level problems (Bullard *et al.*, 1985). To be able to utilize heuristics with continuous variables it is necessary to make some modifications. Uncertainty and risk are integrated in the same way as they were integrated when using heuristics at the forest level. A new approach has been developed in last years (Heinonen *et al.*, 2007; Packalén *et al.*, 2011). In this method the forest is divided into raster cells, so-called dynamic-units, and they are used

in optimization as management units instead of using predefined stand compartments.

The second group of innovative approaches is the one related to the nature of uncertainty. Due to the multifunctionality of forest and the growing involvement of society in forest management, uncertainties coming from the preferences of the decision makers must be considered. Sometimes the DM is not able to quantify his or her preferences; in this case fuzzy set theory (Kangas *et al.*, 2008) must be applied. In other occasions DM cannot or does not wish to express their preferences about different criteria. In this case stochastic multicriteria acceptability analysis (SMAA) is required. When using a priori approaches in objectives problems the DM has to set his preferences for the various objectives without knowing the tradeoffs among them. This limitation can be solved with a posteriori approach: when objectives conflict it may be useful to identify a set of Pareto-optimal or efficient solutions (Tóth *et al.*, 2006; Tóth and McDill, 2008). Knowing the set of efficient solution can help the DM to understand the trade-offs between the competing objectives. This method is called the efficient frontier method and it is very helpful because it is not necessary that the decision maker has to define his preferences beforehand. When the DM knows beforehand which the consequences of a given decision are, he has tools to decide. Risk-efficient frontier has also been employed as a decision tool that can be used to understand the trade-offs between profit and risk.

Based on the portfolio technique, a new method has been widely developed in recent years: robust portfolio model. The portfolio technique is based on the fact that when limited resources are available, different projects must be combined in order to maximise the return and minimise the risk. The robust portfolio model also allows the inclusion of different sources of uncertainty, *i.e.* uncertainty in preferences of the DM, uncertainty in projects performances, uncertainty related the constraints. Including all these sources of uncertainty the method is able to generate a set of feasible portfolios. This method has been employed recently in forest planning (Liesiö *et al.*, 2007) showing great potentialities.

The third category of proposed approaches deals with the way to assess uncertainty. Traditional methods are sensitive to uncertainty characterization, *i.e.* they need to characterize uncertainty in an explicit way in order to be solved. In general, this is a difficult task. To try to solve this shortcoming, different techniques from other fields have been analysed (Eggenberg *et al.*,

2011). For instance, a method based on conservation management studies rises up and seems very helpful to be used in forest planning. This method is the information-gap theory (Ben-Haim, 2001). It addresses the question of how much uncertainty can be tolerated before our decision would change. It assesses the robustness of decisions in the face of severe uncertainty. Different management decisions may result when uncertainty in utilities and probabilities are considered. Information-gap theory consists in three components: the dynamics model, the performance parameter and the uncertainty model. This method has been successfully employed in species conservation management (Regan *et al.*, 2005; Moilanen *et al.*, 2006) and for analyzing the profitability of mixed forests (Knoke, 2008).

Another method that tries to overcome the shortcomings derived from the way to characterise uncertainty is Uncertainty Features Optimisation (UFO) (Eggenberg *et al.*, 2008b). Solutions computed with a model involving an explicit uncertainty set are sensitive to errors in the uncertainty characterization. The UFO framework overcomes these drawbacks by using an implicit modeling of the uncertainty. The advantages are that no uncertainty set characterization is required, saving the modeling effort and protecting against potential errors, and the complexity of the resulting problem is of same order than the original problem.

A very interesting approach is the “option analysis”. The novelty of this methodology is that it is completely different from previous approaches; it presents uncertainty as an opportunity and not as a threat. It is based on “real options” (Neufville, 2003). This term refers to elements of the system that provide rights, instead of obligations, to achieve some goal or activity. The option analysis consists on a set of procedures for calculating the value of options, and specifically of real options, which are the elements of the system that provide flexibility.

With the concept of flexibility a new point of view rises up: uncertainty is not a threat but an opportunity in the sense that it gives value to options. Flexibility provides the opportunity but not the obligation to modify the system to adapt it to the changing environment (Cardin and Neufville, 2008). One option to obtain benefits from uncertainty is by incorporating flexibility when designing a system (Cardin *et al.*, 2007), trying to seek for Flexible Design Opportunities (FDO). It is important not only to identify but also to value these FDO, and there are multiple ways to do it (Cardin and Neufville, 2008). Among the techniques

that have been employed to identify FDO, the interview method seem to be an applicable methodology to incorporate certain sources of uncertainty (wood prices, land use trends, etc.) into the forest planning problem. Screening is also another suitable technique, especially those screening methods that are based on optimizations to identify FDO. This method screens the different design options by combining the design variables in many different ways until a design that maximizes value under certain constraints is found (Cardin and Neufville, 2008). Regarding the methods that value FDO, there are different methodologies that can be applied to forest planning: decision-tree methods (that comprise decision analysis, binomial lattice and enumerative technique) and design transition methods. In the first group decision analysis and enumerative technique considered all the possible combination of solution while binomial lattice reduces the combinatorial space by assuming path interdependence and path recombination. The design transition method finds the design that minimizes lifecycle cost under various scenarios of uncertainty. These methods could be useful when managing stands with low site indexes where it is not worthy to make great investments.

Both uncertainty and flexibility provide great opportunities to the design of successful forest management plans, although very few of the presented techniques have been applied to forest planning problems so far.

## Obstacles in taking uncertainty into account in forest planning and DSSs

Although the concepts of uncertainty and risk and their effects in forest planning decision making have been studied quite extensively, the practical implementations are still very rare in FPSs. Maybe one of the fundamental reasons is that an agreement on the general definition and correct theoretical framework for uncertainty is yet lacking (Kangas and Kangas, 2004). As a result, the whole concept of uncertainty can be well understood in the research community, but not so much among the practical forest planning community.

The methodology for taking uncertainty into account in DSSs has been widely analysed studied extensively and lot of approaches and algorithms have been developed. However, the methods for formulating decision problems involving uncertainty are typically quite complicated and hard to explain for non-specialist (Kangas and Kangas, 2004). This definitely is a hin-

drance to the implementation of the methods, both in research and in practice.

One of the most obvious problems with many of the methods for taking uncertainty into account in decision making is the problem of technical implementation. Some of the approaches for considering uncertainty lead to problem definitions in which the uncertainty space is huge (Sahinidis, 2004). This leads to very large-scale optimization problems and the solving may not be a trivial task. Eriksson (2006) noted that stochastic optimization problems tend to be significantly larger than deterministic ones, which limits the use of the approach. Scenario analysis, which is technically fairly straightforward to implement, can be very time-consuming, which hinders its application (Koutsoukis *et al.*, 2000). Forsell (2009) tested two different stochastic scenario models for mitigating wind damages in Swedish forests. He noticed that the model grows exponentially with the number of stands, polynomially with the number of time periods in the first model, and exponentially with the number of time periods in the second.

Various types of difficulties exist in methods for optimization under uncertainty. One such problem in robust optimization is that the errors are assumed to be uniformly distributed, which denies the use of information about the probability distribution of these coefficients (Palma and Nelson, 2009). Robust portfolio modeling has been tested with problems of relatively small scales and the applicability to larger scale problems is still to be defined (Liesiö *et al.*, 2007). Based on these experiences, there certainly exists a trade-off between relative simplicity and increased complexity when uncertainties are ignored or considered. So far the decisions about considering or ignoring uncertainty have generally been in favor of the simplicity.

Another obstacle in taking uncertainty and risks into account is the knowledge about the uncertainties and risks. Some of the uncertainties are fairly well known, such as inventory errors for some of the most widely used inventory methods. This, however, is not the case everywhere and some of the uncertainties are not adequately known. For example, the errors in forest growth models are not always well-known. Moreover, the probability distributions of the various risks are commonly not known, and need to be approximated. The uncertainties associated with future timber prices are based on historical price information and the future price developments are affected by so many unknown factors that the assumed uncertainty can be considered to be uncertain. Another good example of uncertainties that

are difficult, or even impossible, to define are found in planning problems where some of the decision variables are so-called “non-timber variables”, such as scenic beauty, recreational values, sustainability or biological diversity (Kangas and Kangas, 2004). In addition, the past and present uncertainties may well change in the future, as was noted by Pukkala (1998).

The preferences of the decision-maker, such as the risk attitude, are also difficult to describe in a mathematical programming problem (Kangas and Kangas, 2004). Kurttila *et al.* (2009) commented on Pukkala’s (1998) scenario approach, which considered uncertainties in timber prices, forest growth and decision maker preferences, that it “involves the decision-maker directly specifying the mean and standard deviations, as regards the importance of the objective variables”. In decision making under uncertainty, the subjective attitude of the decision maker, although difficult to describe, has a fundamental role (Yager, 2004).

Many of the MCDM methods are capable of considering various uncertainties, but they too are not without their deficiencies when used in practice. Many of the methods suffer from difficulties in the interpretation of the results. For example, the results of various outranking methods have been noticed to be very difficult to interpret. Multi Attribute Utility Theory (MAUT) —based applications often suffer from problems in handling uncertain information (Kangas *et al.*, 2001), but other problems have been observed as well. Defining the risks and uncertainties precisely may be too difficult task for the decision makers, in this case non-industrial private forest owners, as was noted when applying a MAUT-based risk consideration in fire management planning (Teeter and Dyer, 1986).

The obstacles for uncertainty considerations discussed previously have been more or less technical or related to difficulties in practical implementations. However, other kinds of obstacles for taking uncertainty into account can also be found. One such obstacle is in the attitudes towards uncertainty among the people acting as the decision makers. In some situations the mere existence of uncertainty might be an unfavorable fact. Mowrer (2000) stated that “certainly, no resource manager wants to stand up in a public meeting and admit that they are not quite sure of the exact outcome of a proposed activity”.

In other situations the whole concept of uncertainty might be unfamiliar and vague to the decision maker. The concepts and terms related to uncertainty might be obvious to analysts and scientists, but unclear to

non-experts. Ascough II *et al.* (2008) emphasized that it would be important to develop an appropriate risk-based performance criteria that are understood and accepted by a range of disciplines.

In some decision situations, the existence and nature of the various uncertainties might be known, but the effects of the uncertainties are not considered as too big of a problem. For example, the expected economic losses due to given risk or uncertainty might be considered insignificant, or less than the costs of taking the uncertainty into account. This, of course, depends quite a bit on the decision maker and the decision problem in question. As Mowrer (2000) pointed out, the overall level of acceptable uncertainty in a given decision-making situation is highly subjective. However, if one is to decide whether some uncertainty is worth taking into account or not, the uncertainty and its effects should be known.

## Conclusions

The literature review shows that there is multitude of reasons for considering uncertainty in forest planning. The number of different approaches has shown an important increase in last years. However, the selection of one alternative over another is not an straightforward decision, it would depend on several factors, for instance the scale of the planning process, the type of the problem, the nature of uncertainty, etc. The decision maker should be aware of the different existing methodologies in order to choose the one that better fits to his/her requirements.

Different methods have been developed in order to assess risk and uncertainty in DSSs. However, it is very seldom that the uncertainties are actually considered in FPSs. In order to enhance the inclusion of uncertainty considerations into practice, certain aspects need to be considered.

First of all, it is necessary to have a good understanding of uncertainties and their effects. In this sense, an effort needs to be done in developing models that are able to predict the effects of different sources of uncertainty and risk: inventory error models, growth error models, stochastic timber price models, risk models for natural hazards and so on. Secondly, there should be a motivation for implementing uncertainty considerations. We should have a clear vision about what are the uncertainties that we could and should consider, and what can we gain by considering the

uncertainties and making better decisions. This requires knowledge about the expected losses that are due to the various sources of uncertainty.

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. Preferably the information on the uncertainties should not increase the amount of information the decision makers need to consider significantly. One solution to this would be to integrate the uncertainty considerations into the DSSs so that it is implicitly considered in the decision variables, and the decision maker need not worry about that.

As a final conclusion, uncertainty is something we should take into account in forest planning decisions, and the difficulties in the implementation of the uncertainty considerations are nothing that cannot be solved with some effort.

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## Appendix I. Dimensions definitions

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### Temporal scale

— *Long term (strategic) management planning.* Planning horizon extending over more than 10 years. It may include planning periods of more than 10 years.

— *Medium term (tactical) management planning.* Planning horizon extending from 2 to 10 years. It may include planning periods of more than one year.

— *Short term (operational) management planning.* Planning horizon extending over one year or less. Typically it will include planning periods of one month or less.

### Spatial context

— *Spatial with neighborhood interrelations.* The interactions of decisions made in neighboring stands (or other areal units) are of importance, *i.e.* a decision made in one stand may 1) constrain decisions on neighboring stands or 2) influence the outcome of a decision made in its neighbors (*e.g.* some outcomes may not be measured in a per hectare basis) and . Examples are systems where there is a maximum harvest opening or where outcomes such as types (and amounts) of edge (borders between stands) are considered to address habitat quality or biodiversity concerns.

— *Spatial with no neighborhood interrelations.* We are concerned with the location of forest operations and yet it is assumed that a decision made in one stand does not constrain decisions on neighboring stands and does not influence the outcome of a decision made in its neighbors (all outcomes may be measured in a per hectare basis).

— *Non spatial.* Stands may be aggregated into strata or analysis units without consideration to their mutual location. There is no concern with locational specificity and with neighborhood interrelations.

### Spatial scale

— *Stand level.* Homogeneous unit according to ecological, physiographic and development features.

— *Forest level.* Forest landscape with several stands that belong together for a common purpose.

— *Regional/national level.* A set of landscapes that may be managed each to address different objectives.

### Parties involved

— A single decision maker makes the decision on his/her own, *e.g.* the forest owner.

— One or more decision makers have the power to decide. In addition, there can be other parties with no formal decision-making power that are influenced or may influence the decision (stakeholders).

### Objectives dimension

— *Single.* The management planning problem addresses one and just one objective.

— *Multiple.* The management planning problem addresses two or more objectives, any pairs of which could be conflicting, complementary or neutral with respect to their contributions.

### Goods and services dimension

— *Market non wood products.* The management planning problem addresses the supply of non wood products that are traded in the market (fruits, cork,...).

— *Market wood products.* The management planning problem addresses the supply of wood products that are traded in the market (roundwood, pulpwood, biomass,...).

— *Market services.* The management planning problem addresses the supply of services that may be traded in the market (recreation, hunting, fishing,...).

— *Non market services.* The management planning problem addresses the supply of services that typically are not traded in the market (public goods, aesthetics, water, biodiversity).