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Multiple-use forest planning techniques: a synthesising analysis

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Abstract

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Because of the complexity of multiple use forest management problems, it is difficult to quantify the consequences of management activities and to identify good management plans without the use of mathematical models. On the other hand, such models usually cannot provide sufficiently precise descriptions of the real problem, and thus one should not rely entirely on the solutions of the models to find the best management plan. This 'paradox' has plagued multiple-use forest planning and management. It has also motivated the continual suggestion of new planning techniques in the forestry literature. This paper provides an overview of various multiple-use forest planning techniques that have been proposed, emphasising their strengths and limitations in practical applications. It describes three planning procedures and discusses how alternative techniques can be applied at different stages of the planning process to overcome difficulties associated with each technique.

Keywords: forest resource management, timber harvest decision, nontimber benefits, production possibility frontier, multiple-objective linear programming, goal programming.

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Introduction

A common feature of multiple-use forest management problems is that the outcome involves several attributes that affect the preferences of the decision maker (DM) across a range of management options. Yet there is no easy way of aggregating the quantities, qualities, or both, of different attributes, because many of the non-timber goods are not priced in markets. In order to determine the optimal management plan, one needs to know the DM's preferences. Throughout this paper, we assume that the forest owner is the decision maker, and use the two terms interchangeably. Management decisions for public forests are typically made by forest managers. A forest manager acts on behalf of the forest owners, however. The forest owners (*i.e.* the public) are the ultimate decision makers, and it is their preferences (the social preferences) that determine the optimal management plan. Private forests also generate benefits for many individuals other than the forest owners. These external effects should be taken into account through forest policy measures (*e.g.* taxes, subsidies, forest legislation, *etc.*). As long as society does not impose detailed management plans on private forest owners, it is proper not to include directly social benefits and costs associated with private forest management, in forest management planning.

In multiple-use forest management, as in other multi-attribute decision-making contexts, complete information about the DM's preferences is not available at the outset. Rather, such information needs to be elicited from the DM's subjective judgments. Accordingly, multiple-use forest planning involves the assessment of the DM's preferences and the evaluation of the feasible management plans. There is a large variety of methods that can be used to assess the preferences of the DM, and to evaluate and compare alternative management plans. From the application point of view, a very important, but difficult, task in multiple-use forest planning is to choose among the suitable methods.

The purpose of this paper is to provide an overview of multiple-use forest planning techniques. Of especial interest are three approaches (economic valuation of nonmarket goods, multiple-objective programming, and multiple criteria decision-making), that have been used to support multiple-use forestry decision-making. Smith (1998) surveys the nonmarket valuation methods. The review article by Tarp & Helles (1995) contains a wealth of references to applications of multiple criteria decision-making and multiple-objective programming techniques in forestry. This paper focusses on the relationship between these approaches and their limitations in the context of multiple-use forest planning. It attempts to outline how different approaches can be used together, to help forest owners and managers make better choices of management plans.

There are two basic systems for multiple-use forest management (Dana, 1943; Pearson, 1944). One is *stand-level, multiple-use management* – each stand is managed to produce a combination of timber and non-timber goods that maximise the forest owner's utility or the total value of the stand. This is essentially a stand-level joint-production problem (Gregory, 1955; Hartman, 1976). The other system is *primary-use management* – each stand is managed for a primary use (other uses are permitted if they do not interfere with the primary use), and multiple-use is achieved at forest level by assigning alternative primary uses to different stands. Accordingly, the decisions that need to be made include determination of the primary use and the associated management plan for each stand.

It is much easier to determine the optimal management plan when a stand is managed for a single use, than when it is managed for joint production. Thus the multiple-use management problem can be considerably simplified by assigning a primary use to each stand. Note that a particular stand might be most suitable for one use, while other uses are of little relevance in the stand, or the alternative uses are completely incompatible with each other (Gregory, 1987). Hence primary-use management may be consistent with stand-level multiple-use management under certain circumstances. It is not always the most efficient way of managing the forest for multiple uses, however. Many forest stands are suitable for a number of more or less mutually compatible uses. In such situations, to ignore the trade-offs between different uses implies that the stands are not being managed to produce the optimal combination of goods. On the other hand, stand-level, multiple-use management has been criticised for being impractical and unrealistic (Clawson, 1974). The interactions between the various uses are complex, and not well understood. Because of difficulties in quantifying the non-timber benefits, attempts to manage each and every stand for multiple use may not actually improve the efficiency of forest resource utilisation.

In reality, multiple-use management is usually practised at forest level by means of some combination of the two systems. More specifically, a forest as a whole is managed for both timber production and various non-timber uses, while each stand within the forest may be managed for a primary use or for several uses, depending on the suitability of the stand for different uses and the compatibilities among them. The problem is usually formulated as one of allocating a forest to different management plans using a static model (see, *e.g.*, Leuschner, 1990); or as one of determining the optimal harvest area at different time points, distributed among different age-classes, in a dynamic model (Bowes & Krutilla, 1985, 1989). Either way, the aggregate management plan for a whole forest is determined on the basis of the output of timber and non-timber goods from all stands in the forest. Whether a particular stand should be managed for a primary use or for joint production, is determined implicitly.

In the present paper, we shall consider the multiple-use management problem at both the stand level and the forest level. Single-stand analyses provide important insights into the multiple-use problem, and clarify the implicit assumptions underlying many multiple-use forest planning models. These are discussed in the next section. The third section addresses multiple-use planning at the forest level. The emphasis is on the determination of management plans in multiple-use forestry practices. It describes three planning procedures, and discusses how alternative techniques can be applied at different stages of the planning process, to overcome difficulties associated with each technique. The paper ends with some general comments on quantitative planning techniques, and a brief discussion of sustainable development concerns.

Multiple-use stand management

Following the Faustmann tradition, economic analyses of the single-stand management problem have focussed on the optimal rotation age, *i.e.* the age at which a stand should be harvested and regenerated. Hartman (1976) extended the classical Faustmann model to incorporate the flow of non-timber value from the standing forest into the determination of the optimal rotation age. His argument is that, since a standing forest also provides various environmental services, the rotation age should be chosen to maximise the net present value of both timber and non-timber benefits. Assuming that the non-timber value is a function of stand age, the optimal multiple-use rotation model is

$$\max_T W(T) = \frac{-C + \int_0^T z(t)e^{-rt}dt + p(T)V(T)e^{-rT}}{1 - e^{-rT}} \qquad (1)$$

where C is the regeneration cost, $p(T)$ is the stumpage price at age T, $V(T)$ is the timber volume at age T, r is the discount rate, and $z(t)$ is the value of environmental services from the forest stand at age t. The first-order condition for an interior solution to problem (1) is

$$p'(T)V(T) + p(T)V'(T) + z(T) = rP(T)V(T) + rW(T) \qquad (2)$$

Evidently, the non-timber value affects both the marginal benefit and the marginal cost of delaying harvest. The effects of multiple-use considerations on the optimal rotation age depend on how the non-timber value changes with stand age (Hite, Johansson & Löfgren, 1987; Snyder & Bhattacharyya, 1990).

Although simple, the Hartman model offers several important insights into the multiple-use problem. First, on the basis of the first-order condition (2), it can be shown that if the non-timber value is a monotonically increasing (decreasing) function of stand age, then the optimal multiple-use rotation is longer (shorter) than the Faustmann rotation (Bowes & Krutilla, 1985; Hite *et al.*, 1987). Accordingly, timber supply may decrease (increase) in the short term, but increase (decrease) in the long term, when the non-timber benefits are recognised in management decisions, because the Faustmann rotation usually is shorter than the maximum sustained yield age (Johansson & Löfgren, 1985; Binkley, 1987).

Secondly, a non-timber value that is constant with respect to stand age does not affect the optimal rotation (Bowes & Krutilla, 1985). In this case, the rotation age affects only the present value of timber benefits; thus one should choose the Faustmann rotation. Although one can hardly imagine a situation in which the non-timber benefits are independent of stand age, this result has two important implications. First, it means that higher non-timber values do not necessarily have larger impacts on the optimal multiple-use rotation age. Secondly, it means that a bias in the estimated non-timber values at different stand ages does not change the calculated optimal rotation age. These can be illustrated by adding a constant term a to the non-timber value $z(t)$ at each age. The constant term shifts the net present value curve by a/r, but the derivatives of $W(T)$ with respect to rotation age T, hence the optimal rotation age, remain unchanged. It is the marginal impacts of stand age (forest condition) changes on the non-timber value that affect the optimal decision. As Bowes & Krutilla (1985) point out, to focus only on the relative level of total benefits can be misleading.

Finally, multiple-use considerations alter the impacts of changes in timber prices, regeneration cost, and discount rate on the optimal rotation age and thus on the supply of timber (Bowes & Krutilla, 1985). For example, an increase in timber price may decrease or increase the rotation age, depending on whether the multiple-use rotation is longer or shorter than the Faustmann rotation; an increase in the discount rate may increase or decrease the multiple-use rotation age, while it shortens the Faustmann rotation.

There are few published applications of the Hartman model (Calish, Fight & Teeguarden, 1978; Nguyen, 1979; Englin, 1990; van Kooten, Binkley & Delcourt, 1995; Gong & Kriström, 1999). One reason for this is the difficulty in estimating the non-timber values of a forest stand at varying ages. Another reason is that the assumptions underlying the model can rarely be verified in practical decision situations. Hite *et al.* (1987) show that, to determine the optimal rotation age by means of the Hartman model, one implicitly assumes:

(a) That the utility of the environmental services is independent of the consumption of other goods;
(b) That the utilities at different time points are additively independent, and the rate of time preferences equals the interest rate in a perfect capital market;
(c) That the marginal utility of income is constant (independent of the size of forestry income);
(d) That the utility of the environmental services from each stand is a function of the age of the stand, independent of the condition of other stands in the forest.

The first three assumptions establish net present value maximisation as a correct criterion for multiple-use decision making. The last one enables us to determine the optimal rotation of a forest stand by maximising the net present value, without considering the decision for any other stand in the forest. These assumptions oversimplify the multiple-use management problem, and limit the usefulness of the model for practical purposes. One may argue that these assumptions are reasonable with respect to some environmental services, such as carbon uptake. However, it should be noted that a forest stand usually provides a mix of environmental services, all of which should be considered in the rotation decision.

An apparent weakness – also the most serious weakness – of multiple-use stand management models is that they ignore interdependence among stands. When the various environmental services are considered, the non-timber value of a stand depends not only on its own condition, but also on the conditions of all other stands in the forest. What one does with one stand affects the non-timber values of, and consequently the optimal management decisions for, the other stands (Hartman, 1976). Bowes & Krutilla (1985) presented a multiple-use forest harvest model that takes into account interdependence among stands. They show in a formal way that the optimal harvest ages for different stands are interrelated.

Swallow & Wear (1993) modified the

Hartman model by including the age of a neighboring stand as one determinant of the non-timber value of the stand under consideration. Environmental services from the two stands were considered as substitutes, and the harvest decision regarding the neighboring stand was assumed to be exogenous. Using this modified model, the authors clarified the impacts of stand interaction on the optimal harvest age. Harvesting of the neighboring stand will cause an instant shift in the non-timber value curve of the stand under consideration, which has two offsetting effects on the optimal harvest age of the stand: the marginal non-timber value of increasing the harvest age increases (decreases), while at the same time, the non-timber value of future rotations increases (decreases). Thus the marginal opportunity cost of delaying the harvest of the stand increases (decreases). Depending on the relative magnitudes of these two effects, the optimal harvest age of the stand may increase or decrease when the neighboring stand is harvested.

The extended multiple-use rotation models by Bowes & Krutilla (1985) and Swallow & Wear (1993) are both based on the net present value maximisation criterion. The essential difference between these models and the Hartman model with respect to the DM's preferences, is the following: the extended models explicitly recognise that the utility of the environmental services from one stand is affected by the condition of the other stands, while the Hartman model disregards this dependence.

Kuuluvainen & Tahvonen (1999) examined the rotation decision of non-industrial private forest owners in Finland, and found that the rotation age depends on both the exogenous income and the rate of time preference. This is because the exogenous income and time preference affect the marginal utility of timber harvest profits, which in turn affects the non-timber value and thus the optimal rotation. This result implies that non-linearity in the utility function of income could also lead to interdependence among stands. One might argue that the timber benefits from a single stand constitute only a small part of the forest owner's total income. Thus the marginal utility of income is approximately constant with respect to the choice of rotation age. However, the marginal utility of income, and the non-timber value of each stand, may depend on the income from the other stands.

In short, single-stand analyses, while they provide important insights into the multiple-use forest management problem, impose very restrictive assumptions about the DM's preferences. The value of environmental services from one stand typically depends on the conditions of the neighboring stands, and the optimal decisions for different stands are interrelated. Therefore, multiple-use management problems should be analysed at the forest-level, explicitly to incorporate the interactions between stands.

Multiple-use forest planning

Management activities change the condition of a forest, thereby affecting the quantity, quality, or both, of the environmental services from the forest, hence also their value. In a theoretical analysis, it is often sufficient to express the value of environmental services from a forest as a general function of the forest condition. To determine numerically the optimal management plan for a particular forest, however, one should quantify the impacts of changes in forest conditions on the value of the environmental services. The quantity, quality, or both, of the environmental services from a forest depends on a wide range of forest characteristics, *e.g.* the age-structure, the spatial distribution, and the management history of the forest. Moreover, market prices for the environmental services typically do not exist. These factors make it difficult to establish an explicit functional relationship between the non-timber value of a forest and the forest condition descriptors. Because of the lack of empirical non-timber value functions, one must assess the DM's preferences over the range of possible management outcomes, in order to find the optimal management plan.

A forest can be used for various purposes, such as timber production, recreation, hunting, wildlife protection, soil and water conservation, and so on. Alternatively, we say that a forest can be managed to produce a variety of goods, whereby the output of each good depends on how the forest is managed. The use of a forest for one purpose does not preclude the possibility of using the forest for some other purposes (at least, one can allocate one part of the forest to each use). Thus, all the potential uses of importance to the forest owner should be considered in forest management decisions. What uses are relevant, and, in particular, the relative importance of different uses, may change from case to case. In the discussion which follows, we consider a general multiple-use management problem, whereby a forest is managed to produce timber and a number of non-timber goods, without specifying the non-timber goods.

The different uses of the forest are not perfectly compatible with each other, in the sense that increasing the output of one good would usually reduce the output of some other goods. Moreover, different goods are not perfect substitutes, in the sense that the rate at which the forest owner is willing to trade one good for another changes as their outputs change. The forest can be managed according to one of many feasible plans. Each management plan is associated with a different set of outputs of timber and non-timber goods. The decision problem is to find among the feasible management plans the one that gives the most preferred outputs of different goods.

Although it is not explicitly stated in the literature, multiple-use forest planning usually follows one of three procedures: top-down, bottom-up, or interactive. The top-down procedure starts by assessing the DM's preferences, and proceeds to evaluate the feasible management plans. According to the bottom-up procedure, the feasible management plans are evaluated first, on the basis of the most easily accessible preference information (*i.e.* whether more is preferred to less or less is preferred to more, as regards each attribute of the management outcome). Management plans selected through the preliminary evaluation are then compared on the basis of a more comprehensive assessment of the DM's preferences. Finally, the interactive procedure is a process of alternate preference assessment and management plan evaluation. Information about the DM's preferences is used to identify an efficient management plan. The management plan is presented to the DM, to elicit more accurate information about the preferences. In general, the process continues until the sequence of generated management plans stabilises, or until a satisfactory management plan has been found. The next section reviews the planning techniques according to each of these procedures.

The top-down procedure

The top-down approach in multiple-use forest planning assumes that the preferences of the DM can be elicited at the beginning of the planning process. When the DM's preferences are known, the major task of planning is to identify and evaluate the feasible management plans, to find the most preferred one. Since preferences may be expressed in different ways, a number of optimisation models has been applied to determine the optimal management plan.

Utility maximisation model

In principle, a DM's preferences in a multiple-use context can be described by a multi-attribute utility function, and the decision problem can be formulated as one of finding a feasible management plan that maximises the utility of the DM. To calculate the utility associated with a management plan, one should determine the optimal consumption over time, since the monetary income can be reallocated among different time periods through the capital market. Note that, in general cases, the utility of the non-timber goods and the utility of income are not additively independent, implying that the optimal consumption over time depends on the flow of non-timber goods. Therefore, the forest management plan and the consumption decision should be optimised simultaneously

$$\max_{x,c} \sum_{t=1}^{T} U(c_t, z_{1t}, \ldots, z_{nt})e^{-\rho t}$$
$$\text{s.t.} \sum_{i=1}^{T} c_t e^{-rt} = f_0(x)$$
$$z_{it} = f_i(s_t(x)) \quad \text{for } i=1, \ldots, n;\ t=1, \ldots, T \tag{3}$$
$$x \in X$$

where $U()$ is the utility function, T is the planning horizon, c_t is the consumption in time period t, r is the interest rate, ρ is the rate of time preference, $f_0(x)$ is the present value of current and future profits, $s_t(x)$ is the forest condition in period t, and $z_{it} = f_i(s_t(x))$ is the output of non-timber good i in period t that is associated with management alternative x, and X is the set of feasible management plans.

To apply the utility maximisation model (3), one should estimate the utility function of the DM as well as the non-timber good production functions. For publicly owned forests, the utility function used to compare alternative management plans should represent the preferences of society. In other words, one should choose the management plan that maximises social welfare (some aggregate measure of the utilities of all individuals in a society). The difficulties involved in quantitatively assessing the social welfare function are widely recognised. The model could be applied to private forest planning. Even in this case, the usefulness of the method is limited. Because of the complex spatial interactions between stands, the non-timber good production functions can be estimated only very roughly. Therefore, it may not be worthwhile to estimate the utility function, which is in itself difficult, and to determine the optimal management plan by direct maximisation of the DM's utility.

Net present value (NPV) maximisation model

Analogous to the analysis of Hite *et al.* (1987), it can be shown that NPV maximisation is a correct criterion for determining the optimal multiple-use management plan under the following assumptions: *(a)* the utility of the environmental services is independent of the consumption of market goods, *(b)* the marginal utility of income is constant, and *(c)* the rate of time preference equals the interest rate in a perfect capital market. Given these assumptions, the management plan that maximises the utility of the DM also maximises the NPV of the timber and non-timber benefits. Since the non-timber benefits of a forest to its owner or to society can be estimated in monetary terms (see, *e.g.*, Johansson (1987) for a general discussion of the theory and methods of non-market valuation), NPV maximisation provides a practically applicable method for multiple-use planning of public as well as private forests.

One way to calculate the value of a non-timber good is to multiply the output of the non-timber good by its shadow price. Accordingly, the NPV maximisation model can be formulated as:

$$\max_{x \in X} \sum_{t=1}^{T} \left[p_t h_t(x) - C_t(x) + \sum_{i=1}^{n} p_{it}^{e} f_i(s_t(x)) \right] e^{-rt} \tag{4}$$

where p_t is timber price in period t, $h_t(x)$ is the volume of timber harvested in period t, $C_t(x)$ is the management cost in period t, $s_t(x)$ is the forest condition in period t, $f_i(s_t(x))$ is the output of non-timber good i in period t, and p_{it}^{e} is the shadow price of non-timber good i in period t.

Technically, it is relatively easy to apply this model. The shadow price of a non-timber good equals the DM's marginal willingness-to-pay (WTP) for the non-timber good, which can be estimated by using, for example, the contingent valuation method (Mitchell & Carson, 1989). The output of each non-timber good $f_i(s_t(x))$ can be approximated, *e.g.* by means of a linear production function. This information enables us to solve numerically the NPV maximisation model.

However, it should be noted that even if the outputs of non-timber goods can be determined exactly, the optimal solution to the NPV maximisation problem (4) is not necessarily the optimal forest management plan. The problem lies in the interactions between the optimal model solution and the shadow prices of the non-timber goods. It is clear that the solution to problem (4) depends on the shadow prices of the non-timber goods. On the other hand, the marginal WTP of an individual for a non-timber good depends, among other things, on the quantity of the non-timber good (see, *e.g.*, Mattsson (1990)), which implies that the shadow prices of the non-timber goods may vary both over time and among different management plans. In application, one usually estimates the marginal WTP conditional on the current outputs of the non-timber goods (or on the current forest condition). NPV maximisation based on such estimations often does not lead to the optimal management plan.

Fig. 1 illustrates this problem of NPV maximisation, by means of a simple multiple-use example involving one non-timber good beside timber. In this figure, timber benefits are expressed in monetary terms. Thus the negative of the slope of the indifference curve gives the marginal WTP for (the shadow price of) the non-timber good and, given a shadow price, NPV maximisation is achieved at the point at which the slope of the production possibility frontier equals the negative shadow price. Evidently, the optimal decision is indicated by point 'O'. Suppose that the current output of the non-

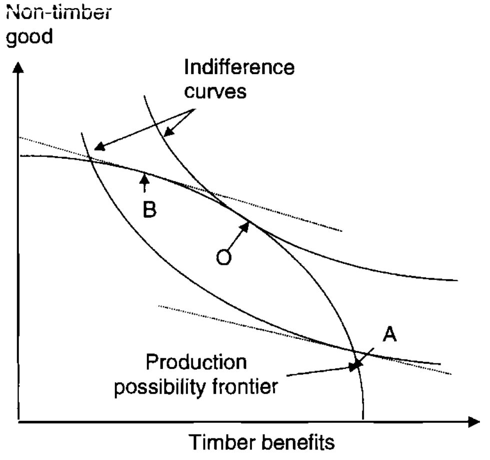

Fig. 1. A possible result of NPV maximisation. Point A is the current outcome, point O is the optimal outcome, and point B is the NPV maximisation decision.

timber good is 'small' (point A). Then the DM's marginal WTP for the non-timber good is high, and NPV maximisation based on this high WTP would lead to an 'optimal' solution, denoted by point B, which implies producing too large an output of the non-timber good. Conversely, if the current output of the non-timber good is 'large', then the marginal WTP would be low, and NPV maximisation based on the estimated marginal WTP would result in too small an output of the non-timber good.

Johansson, Löfgren & Mäler (1989) show that the solution to problem (4) gives the optimal management plan, if the price of each non-timber good equals the DM's marginal WTP for the non-timber good, estimated at the optimal level of output of the non-timber goods. Therefore, one cannot find the optimal management plan without knowing the correct shadow prices of non-timber goods. Yet the correct shadow prices can be estimated only if the optimal outputs of the non-timber goods are known. This interdependence provides some hints as to how the correct shadow prices and the optimal forest management plan can be determined interactively. We shall return to the interactive procedure later in this paper.

Linear programming (LP) model

LP models for multiple-use forest planning are straightforward extensions of the LP-based timber management (harvest scheduling) models. Similarly to timber management, the major choices in multiple-use management are the timing and intensity of silvicultural activities and the timing of the final harvest for different stands. Thus it is natural to extend a timber-management model to take into account concerns about the non-timber uses of the forest. One way of incorporating multiple-use considerations into a timber-management model, is to restrict the feasible choices of management plans. Assume that there is a satisfactory level of output of each non-timber good. One can then formulate the multiple-use management problem as one of choosing a management plan which produces a satisfactory output of each non-timber good, and which maximises the timber benefits (Leuschner, Porter, Reynolds & Burkhart, 1975).

$$\begin{aligned} &\max_x \; c_0 x \\ &\text{s.t. } c_k x \geq g_k \quad \text{for } k = 1, \ldots, n \\ &\quad A x \leq b \\ &\quad x \geq 0 \end{aligned} \tag{5}$$

where c_0 is a vector of coefficients in the objective function related to timber production, x is a vector of decision variables, A is a matrix of technical coefficients, b is a vector of available resources, c_k is output of product k associated with management alternative x, g_k is the satisfactory level of output of non-timber good k, and n is the number of non-timber goods.

The LP model (5) is a simple, but very rigid formulation of the multiple-use planning problem. By including the non-timber-use constraints in the model, one neglects the trade-offs between different uses of the forest. On the one hand, the model implicitly assumes that the achievement of the specified output level of each non-timber good is immeasurably more desirable than increasing the timber benefits. It is possible that the non-timber-use constraints are so restrictive that the model does not have a feasible solution. On the other hand, only the timber benefits are considered when choosing among the feasible management plans. This would be proper, if the marginal utility of increasing the output of each non-timber good from its lowest acceptable level, were zero.

One can use LP model (5) to identify the optimal management plan if the optimal outputs of the non-timber goods are known. In reality, however, the optimal outputs of the non-timber goods usually remain unknown until the optimal management plan has been found. Another way to take into account concerns about the non-timber uses of a forest, is to change the criterion of choice among the feasible timber management plans. Within the LP framework, this is accomplished by maximising the weighted sum of timber benefits and the outputs of different non-timber goods.

$$\max_{x} \sum_{k=0}^{n} w_k c_k x$$
$$\text{s.t. } Ax \leq b \qquad (6)$$
$$x \geq 0$$

where w_k is the weight assigned to non-timber good k.

Note that the NPV maximisation model (4) is a special case of LP model (6). The major difficulty in applying this model lies in determining correct weights (*i.e.* the relative importance of different uses of the forest).

Goal programming (GP) model

GP was introduced into forest management in the early 1970s, and has been a popular method for multiple-use forest planning (Field, 1973; Flick, 1976; Schuler, Webster & Meadows, 1977; Dyer, Hof, Kelley, Crim & Alward, 1979; Chang & Buongiorno, 1981; Arp & Lavigne, 1982; Mendoza, 1987). Two aspects of the method make it attractive. First, a GP model can be solved as an ordinary LP problem, for which there are effective solution algorithms and computer programs. Secondly, the method builds upon a simple and intuitively clear measure of the preferences of the forest owner(s). One can claim that, in general, a forest owner, by choosing among different management plans, attempts to achieve the maximum timber benefits and the most desirable outputs of the non-timber goods from the forest. Such an ideal outcome can be viewed as the goal at which the forest owner aims. The goal levels of timber benefits and outputs of all non-timber goods usually cannot be achieved simultaneously. Clearly, however, the closer the outcome is to the goal, the more preferable is the underlying management plan. GP identifies the feasible outcome (and the associated management plan) that is closest to the goal, where the distance is measured by the (weighted) sum of deviations from the goal levels.

Mendoza (1987) provides an overview of different GP formulations, and discusses the weakness of the technique. From the practical point of view, a major limitation of GP, as a multiple-use forest planning tool, relates to the need for specifying the goal levels corresponding to different uses of the forest and the weights associated with deviations from the goal levels. The difficulty in determining the weights associated with the deviation from the goal in different dimensions (directions) is evident. As regards the setting of goal levels, it should be noted that there is no simple way correctly to integrate the output of a non-timber good over time into one goal level, while it is highly impractical to set a goal level corresponding to the output of the non-timber good in each time period. Developments have been made to overcome these difficulties and to improve the efficiency of GP (Hotvedt, Leuschner & Buyhoff, 1982; Walker, 1985; Mendoza, 1986). Mendoza (1987) reviews the applications as well as the new developments of traditional goal programming methods in forestry.

De novo programming

In essence, *de novo* programming is a new (and innovative) way of using the LP technique rather than a new planning tool. The key difference between *de novo* programming and standard LP is that the latter optimises the utilisation of a given set of resources of fixed quantities, whereas the former recognises the possibility of trading between different types of resources, and simultaneously determines the optimal quantities and allocations of different resources. This difference can best be explained by a simple example. Suppose that there are three types of resource (referred to as A, B, and C) of 12, 10, and 8 units, respectively, which can be used to produce two products, I and II. The problem is to determine the output of each product so that the profit is maximised. It requires 2 units of resource A, 1 unit of resource B, and 1 unit of resource C to produce 1 unit of product I. Production of 1 unit of product II requires 1.5 units of resource A, 2 units of resource B, and 1 unit of resource C. The profit of producing 1 unit of product I is 30, and the unit profit for product II is 35. The LP formulation of the problem is

$$\max_x \ 30x_1 + 35x_2$$

$$\text{s.t.} \ 2x_1 + 1.5x_2 \leq 12$$
$$x_1 + 2x_2 \leq 10$$
$$x_1 + x_2 \leq 8$$
$$x_1, x_2 \geq 0$$

The optimal production plan is to produce 3.6 units of product I and 3.2 units of product II, and the associated profit is 220. With this production plan, resources A and B are used completely while 1.2 units of resource C are left.

If one can exchange one type of resource for another, then each type of the resources can be viewed as part of a 'production budget'. In such a case, the production plan should be optimised simultaneously with the allocation of the production budget among different resources, which is exactly what *de novo* programming does. Assume that the unit prices of resources A, B, and C are 4, 5, and 8, respectively. The initial allocation of resources is equivalent to a production budget of 162. The *de novo* programming formulation of the problem is

$$\max_x \ 30x_1 + 35x_2$$

$$\begin{aligned} \text{s.t.} \ & 2x_1 + 1.5x_2 \leq b_1 \\ & x_1 + 2x_2 \leq b_2 \\ & x_1 + x_2 \leq b_3 \\ & 4b_1 + 5b_2 + 8b_3 \leq 162 \\ & x_1, x_2, b_1, b_2, b_3 \geq 0 \end{aligned} \tag{7}$$

The optimal solution is: $x_1^* = 0$, $x_2^* = 6.75$, $b_1^* = 10.125$, $b_2^* = 13.5$, $b_3^* = 6.75$, and the maximum profit is 236.25. In practice, this entails selling 1.875 units of resource A and 1.25 units of resource C, and buying 3.5 units of resource B. By reallocating the production budget, one increases the profit by more than 7%.

From the LP formulations (5) and (6) of the multiple-use forest planning problem, one can see that there are two possible situations in which *de novo* programming could be used (see Bare & Mendoza, 1988, 1990 for illustrations). The first is when some or all of the initially given resources are flexible, *i.e.* some component can be exchanged for others. In this case, one can reformulate the resource constraints $Ax \leq b$ to determine the optimal quantities of different resources, as illustrated by the above example. However, the application of *de novo* programming does not solve the basic problem of multiple-use planning (the difficulties and weaknesses of the LP models remain).

Secondly, *de novo* programming can be used to deal with the trade-offs (within limited ranges) between different non-timber uses, if the shadow prices of the non-timber goods are known. Knowing these prices, one can integrate the non-timber use constraints in LP model (5) into one non-timber value constraint. Through the integration of the non-timber use constraints, the output of each non-timber good becomes flexible (one can increase the output of one good to compensate for a decrease in another). This will expand the set of feasible management plans, which in turn may increase the maximum timber benefits. Such an application of *de novo* programming requires information about the prices and the lowest acceptable value of the non-timber goods produced in a forest, and consequently is no easier than using one of the LP models. Moreover, if one has estimated the prices of the non-timber goods, then one can use the LP model (6) to find the management plan that maximises the sum of timber benefits and the values of the non-timber goods. It does not seem reasonable to maximise the timber benefits subject to a constraint on the non-timber value.

Fuzzy programming

The planning models discussed above commonly assume that both the set of feasible management plans and the outcome associated with each management plan are known with certainty. However, the certainty assumption is usually not satisfied in reality, nor can it be fully justified. Uncertainties exist in the current state and the dynamic process of the forest, in future timber prices and management costs, and in the DM's preferences. The complex interactions between different stands typically cannot be described precisely in the non-timber good production functions. Therefore, a real-life planning problem may not be precisely defined in the context of traditional planning models, such as those presented above. First, a management plan that satisfies all the constraints may actually be infeasible, and a management plan that slightly violates some of the constraints may prove to be feasible. Secondly, given a management plan, one cannot expect that the realised outcome would always be the same as what is estimated. Since the traditional planning models (*e.g.* 5 or 6) are formulated to find the solution that strictly satisfies all the constraints and maximises the objective function, they are often criticised for being too rigid (Cocklin, 1989b; Mendoza & Sprouse, 1989).

In the context of multiple-use forest planning, fuzzy programming is a simplified approach to dealing with uncertainties in the functional relationships and in the coefficients of the traditional planning models. The rationale behind this approach is as follows: Since the decision space (the set of feasible management plans) is vaguely defined, our knowledge about the feasibility of a management plan varies. While we may be quite sure that some management plans are feasible (or infeasible), we cannot tell definitely whether the others are feasible or not. Obviously, unless the DM is absolutely risk-averse, he should consider not only the management plans that surely are feasible, but also (some of) those that may be feasible (and thus may also be infeasible). It is then necessary to distinguish between management plans, not only in terms of the objective function value, but also in terms of the 'degree of feasibility' (or the probability of being feasible). Thus, for two management plans x and y, that have the same outcome or objective function value, x is superior to y if x has a higher degree of feasibility than y.

Likewise, while recognising the potential errors in the objective function and, in particular, uncertainty in terms of the feasibility of management plans, the management plan (x^*) that maximises the objective function is not guaranteed to be optimal. A management plan that has an objective function value lower than the maximum may turn out to be superior to x^*. Instead of strictly maximising the objective function, it is reasonable to specify a range of satisfactory levels of the objective function value, and to interpret the objective function value associated with a management plan in terms of the conditional probability (given that the management plan is feasible) that the realised outcome is satisfactory. Such an interpretation allows a trade-off between the probability that the chosen management plan is feasible, and the probability of obtaining a satisfactory outcome. On the basis of these arguments, one may view the planning problem as consisting in finding the management plan which has the maximum joint probability (1) that it is feasible, and (2) that it leads to a satisfactory outcome.

One may find that the above description is more suitable for chance-constrained programming (see Charnes & Cooper, 1963; Hof & Pickens, 1991) than for fuzzy programming, but there is a clear parallel between the two techniques. In the forest planning context, it is more intuitive to interpret fuzzy programming in terms of uncertainty and probability, instead of using the fuzzy set concept.

Note that descriptions of fuzzy programming in general do not explicitly use the concept of probability. Instead, feasible decision options and satisfactory outcomes are described in terms of fuzzy sets, and membership functions are used to determine the degree of membership of a decision option (or the associated outcome) in a fuzzy set. Let $g_0{}^l$ and $g_0{}^u$ be the lowest acceptable and the target levels of timber benefits, respectively. Let $g_k{}^l$ and $g_k{}^u$ ($k=1, 2, ..., n$) denote the lowest acceptable and satisfactory levels associated with the output of non-timber good k. Assuming a linear form of the membership functions, a fuzzy programming formulation corresponding to the LP model (5) is

$$\begin{aligned} &\max \lambda \\ &\text{s.t.} \ -\lambda(g_k^u-g_k^l)+c_k x \geq g_k^l \quad \text{for } k=0, 1, ..., n \\ &\quad \lambda(b^u-b^l)+Ax \leq b^u \qquad\qquad (8) \\ &\quad \lambda, x \geq 0 \end{aligned}$$

where b^l and b^u can be viewed as the conservative and optimistic estimates, respectively, of the available resources. Interested readers are referred to Mendoza & Sprouse (1989), Bare & Mendoza (1992), Mendoza, Bare & Zhou (1993), and Ells, Bulte & van Kooten (1997), for more detailed descriptions of different fuzzy programming formulations in multiple-use forestry, and for additional references. The fuzzy formulation (8) in itself is a deterministic LP model, and its solution is the one that strictly satisfies all the constraints and simultaneously maximises the objective function value. More precisely, the model identifies such a management plan that its lowest degree of membership in the fuzzy sets is maximised. Indeed, one can interpret model (8) as a joint-probability maximisation problem, since a higher degree of membership of an element in a fuzzy set naturally implies a larger probability that the element belongs to the set.

Although fuzzy programming models were proposed as flexible alternative formulations to the traditional deterministic planning models, it should be pointed out that the solution of a fuzzy programming model is as rigid as the solution of a traditional deterministic planning model. Since the feasibility of the optimal management plan identified by using fuzzy programming is not guaranteed, the question is what should be done if the identified management plan proves to be infeasible, especially if the resource constraints are violated? Another limitation of fuzzy programming as a planning tool relates to the fact that a choice of management plan is based only on the degrees of membership. For example, it seems more appropriate to use the expected outcome, estimated using the product of the degree of membership of a management plan and the associated objective function value, as the decision criterion.

The bottom-up procedure

In contrast to the top-down procedure, the bottom-up procedure starts with a preliminary evaluation of the feasible management plans, based on limited information about the DM's preferences. The main purpose of the preliminary evaluation is to assess the potentials of various uses and determine the trade-offs between different uses of the forest, or to depict the production possibility frontier. These potentials and trade-offs give a concrete picture of the multiple-use possibilities, which can help to obtain more reliable information about the DM's preferences (*e.g.* better estimates of the relative importance of different uses). The next step in the bottom-up procedure is to assess the DM's preferences, and to determine the optimal management plan. One way to do this is first to make a comprehensive assessment of the DM's preferences with regard to all attributes of the management outcome (*i.e.* the various uses of the forest), based on the results of the preliminary analysis; then to use the preferences to identify the most preferred management plan. Alternatively, one can elicit the satisfactory levels of timber benefits and of the non-timber goods from the DM, generate a finite number of satisfactory management plans, and then determine the optimal choice among the generated alternatives. This section describes and discusses several approaches to estimating the production possibility frontier, to generating satisfactory management plans, and to determining the optimal choice among the generated management plans.

Estimation of the production possibility frontier

A multi-objective linear programming (MOLP) formulation: In forest management literature, multiple-use forest management is often viewed as a multiple-objective management problem. The multiple-objective characteristics of the problem are quite evident in public forest management, where each interest group has its own objective (*i.e.* to maximise its own benefits from the forest). For a privately owned forest, the management objective is to maximise the benefits for the forest owner (within the frame of forestry regulations). Yet timber production and various non-timber uses can be viewed as different sub-objectives of the forest owner. It is therefore natural to consider multiple-use planning as a multi-objective programming problem, for which a large variety of solution methods is available.

MOLP is a commonly used multi-objective programming technique in multiple-use planning, mainly because it is relatively easy to apply this technique to real-life planning problems. A general MOLP formulation of the multiple-use planning problem is

$$\max_{x} \; [c_0x, c_1x, c_2x, ..., c_nx]$$

$$\text{s.t. } Ax \leq b \qquad (9)$$

$$x \geq 0$$

where c_k, $k=0, 1, 2, ..., n$, is a row vector of the coefficients of objective function k, A is the technical coefficients matrix, b is a vector of available resources, and x is a vector of decision variables that specify a management plan.

By maximising each of the objective functions separately, we obtain the maximum values of the objective functions $g_0^*, g_1^*, g_2^*, \ldots, g_n^*$. The point $g^* = (g_0^*, g_1^*, g_2^*, \ldots, g_n^*)$ in the objective function space is called the ideal point (Zeleny, 1974). If the ideal point is attainable, *i.e.* if there is such a management plan $x^* \geq 0$ that $Ax^* \leq b$ and $g_k^* = c_k x^*$ for $k=0, 1, 2, ..., n$, then x^* is the optimal solution of problem (9), which can be found by maximising any of the objective functions. Unfortunately, the ideal point usually is not attainable, implying that there are conflicts between different objectives. For example, maximisation of the timber benefits usually reduces the non-timber values of the forest.

Because of the possible conflicts between different objectives, a MOLP problem typically does not have a single, optimal solution. The optimal or best compromise solution depends on the preferences of the DM. Without complete information about the DM's preferences, one usually distinguishes the feasible solutions between efficient and inefficient solutions. A solution x is efficient (also called pareto-efficient, non-inferior, or non-dominated) if there does not exist another feasible solution x', such that $c_k x' \geq c_k x$ for $k=0, ...,$ n and $c_k x' > c_k x$ for at least one k. In the context of multiple-use forest planning, the set of efficient solutions, when described in the objective function space, corresponds to the joint-production frontier. It is evident that, independent of the preferences of the DM, the optimal solution belongs to the efficient set, which can be determined or estimated without requiring additional information about the preferences of the DM. This property of the efficient set makes MOLP a suitable approach to the preliminary evaluation of multiple-use management plans.

Given the purposes of the preliminary evaluation of management plans, it is proper to describe the feasible set as well as the efficient set in the objective function space. For a MOLP problem, the set of feasible solutions is convex, and the efficient set can be approximated by a finite number of efficient solutions or efficient extreme points and their convex combinations.

Constraint method: One approach to generating efficient solutions of (9) is to maximise one of the objective functions, while treating the others as constraints to be satisfied. That is, to reformulate and solve the problem as a single-objective LP problem of the form (5). By solving the single-objective LP problem with varying right-hand sides of the objective function constraints, one can obtain different efficient solutions spreading over the entire efficient set (Cohon, 1978).

When it is used to estimate the set of efficient solutions, the constraint method has an inherent inefficiency, in that the optimal solution of the single-objective LP problem is not necessarily an efficient extreme-point solution of the original MOLP problem. In addition, this method does not provide an efficient way of controlling and improving the precision of the estimated set of efficient solutions. The problem is that there is no simple way of determining the right-hand sides of the objective function constraints, so that each efficient solution generated would lead to a maximum reduction of the approximation error.

Weighting method: Another straightforward generating method is to form an aggregate objective function by taking the weighted sum of the $n+1$ objective functions. In this way, one reformulates the MOLP problem (9) as an LP problem of form (6). The optimal solution of the LP problem is an efficient solution of the original MOLP problem. By changing the weights, different efficient solutions can be found, which can then be used to form an approximation of the entire efficient set (Steuer, 1976). The weighting method, when the weights are determined heuristically as suggested by Steuer (1976), has the same limitation as the constraint method. However, as we shall shortly describe, the method can be modified so as effectively to generate arbitrarily good approximations of the efficient set.

Multicriteria simplex method: The method is a generalisation of the simplex method for solving standard LP problems (Zeleny, 1974). It generates all efficient extreme-point solutions of the MOLP problem, on the basis of which one can determine the efficient set exactly. Gong (1992) applied this method to a small multiple-use planning problem, with two objectives and a small number of feasible management plans. A major weakness of the method is the lack of a thoroughly tested computer program that is capable of solving large problems.

Non-inferior set estimation (NISE) method: The NISE method (Cohon, 1978) is an iterative weighting method that generates inner and outer approximations of the efficient set. Like the weighting method described above, the NISE method also replies on the optimal solutions of a single-objective LP problem that maximises the weighted sum of the objectives in the original MOLP problem. The main difference between the two methods is that the NISE method determines the weights iteratively, on the basis of the generated efficient solutions. The method was first developed for the two-objective case, and can be most clearly described using a two-objective LP problem. Reformulate a two objective LP problem as

$$
\begin{aligned}
\max_{x} \; & w_1 g_1 + w_2 g_2 \\
\text{s.t. } & g_1 = c_1 x \\
& g_2 = c_2 x \\
& Ax \leq b \qquad\qquad (10) \\
& x \geq 0
\end{aligned}
$$

First, one solves the LP problem (10) with weights ($w_1 = 1$, $w_2 = 0$), and denotes the optimal solution by point $\mathrm{A} = (g_1{}^1, g_2{}^1)$ in the objective function space, see Fig. 2 (if multiple optima exist, choose that which has the maximum value of objective value g_2). Then, one solves the problem with weights ($w_1 = 0$, $w_2 = 1$), and denotes the solution by point $\mathrm{B} = (g_1{}^2, g_2{}^2)$. The ideal point of the MOLP problem is $\mathrm{I} = (g_1{}^1, g_2{}^2)$.

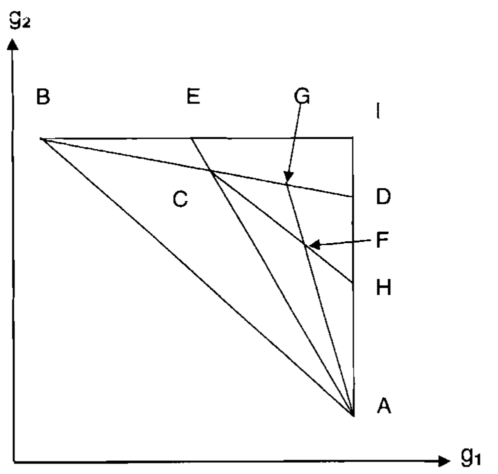

Fig. 2. A graphical description of the NISE method. Points A, B, C, and F represent four efficient solutions. The three triangles BEC, CGF, and FHA provide an approximation of the efficient solution set.

These three points provide a first approximation of the efficient set, which is a concave, stepwise linear curve lying in the triangle ABI. Thus the distance between point I, and the line passing through points A and B, gives an upper bound of the approximation error. The line segment AB is a lower boundary (also called an inner approximation) of the efficient set, and line segments AI and IB form an upper boundary (an outer approximation) of the efficient set. Note that every solution on the lower boundary is feasible, although they are not necessarily all efficient. On the other hand, the upper boundary lies outside the feasible set, unless it coincides with the lower boundary.

Given the two efficient solutions A and B, the most effective way of generating a better approximation of the efficient set is to find the efficient solution that lies as far as possible from line AB. This efficient solution is found by solving the LP problem (10) with weights w_1 and w_2, such that $-w_1/w_2$ equals the slope of line AB. Denote this solution by $\mathrm{C} = (g_1{}^3, g_2{}^3)$. The two triangles ACD and BCE provide a second and better approximation of the efficient set. Note that, if the LP problem has multiple optimal solutions, then all the optima would lie on the line segment AB, implying that line segment AB is the efficient set. The upper bound of the approximation error is the maximum of the distance from point D to line AC and the distance from point E to line BC. Suppose that the distance from point D to line AC is longer than the distance from point E to line BC. One can find the efficient solution that lies as far as possible from line AC, by solving the LP problem (10) with weights w_1 and w_2, such that $-w_1/w_2$ equals the slope of line AC. With this efficient solution, denoted by $\mathrm{F} = (g_1{}^4, g_2{}^4)$, one obtains a third and even better approximation of the efficient set (the three triangles BEC, CGF, and FHA). The upper bound of the approximation error is further reduced. In this way, better and better approximations can be generated, until the required accuracy is reached.

Allen (1986) applied the NISE method to a regional forest planning problem with two objectives. For the two-objective case, this method is both effective and straightforward. In particular, a graphical presentation of the results shows clearly the goodness of the approximations and the trade-offs between the two objectives. When the number of objectives increases, however, the amount of computation required for generating a good approximation of the efficient set increases quickly, and it becomes difficult to visualise the approximated efficient set. On the other hand, a forest planning problem that involves many management objectives is complicated, and thus one cannot expect that it will be easy to estimate the set of efficient management plans or efficient multiple-use combinations.

Generation of satisfactory management plans

Given an approximation of the efficient set, one could directly evaluate the efficient solutions on the basis of a comprehensive assessment of the preferences of the DM, in order to find the optimal management plan. For practical reasons, however, it is desirable to reduce further the possible choices to a finite number of satisfactory management plans before making the final choice. First, a real-life multiple-use planning problem cannot be described precisely by a multi-objective programming model (Mendoza, Bare & Campbell, 1987; Campbell & Mendoza 1988; Cocklin, 1989a). In addition to uncertainties in the functional relationships and in the coefficients of planning models, some important issues may be omitted or cannot be properly incorporated into the planning model, because of the complexity of the multiple-use forest management problem. Consequently, the best choice among the efficient solutions of a MOLP problem is not necessarily the truly optimal management plan. Instead of limiting the possible choices within the efficient set, it is necessary to consider some (significantly) different management plans that are close, in the modelled objective function space, to the best efficient solution. Secondly, because we cannot measure the preferences of the DM exactly, in practice it is often easier to make a more confident choice among a finite number of management plans than from infinitely many management plans.

On the basis of these arguments, it is reasonable to use the approximated efficient set to determine a satisfactory level of each of the modelled objectives, rather than to determine directly the optimal management plan. These satisfactory levels, together with the approximation of the efficient set, define a set of satisfactory management plans in the objective function space (see Fig. 3). The next step is to generate a

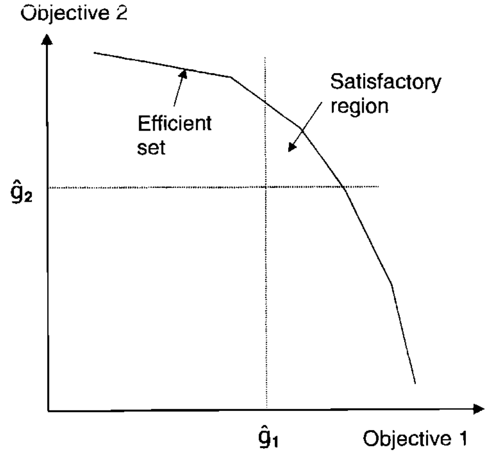

Fig. 3. The set of efficient solutions and the satisfactory region ($\hat{g}_1$ and $\hat{g}_2$ are the satisfactory level of the respective objective).

number of widely different management plans that belong to the satisfactory set. Finally, one evaluates the generated options to find the optimal management plan.

Modelling to generate alternatives (MGA) is a general approach to generating alternative solutions of a MOLP problem that are both satisfactory with respect to the modelled objectives, and different in the decision space. The basic MGA techniques generate different solutions either by minimising the sum of the basic (*i.e.* non-zero) decision variables in the previous solution (Brill, Chang & Hopkins, 1982), or by maximising the sum of a number of randomly selected decision variables (Chang, Brill & Hopkins, 1982), while the satisfactory requirement is met by formulating the objective functions of the original MOLP model as constraints. Both MGA techniques have been described and illustrated in the context of multiple-use forest planning (Mendoza *et al.*, 1987; Campbell & Mendoza, 1988).

The optimisation problem corresponding to the first MGA technique is

$$\begin{aligned} &\min_x D = \sum_{r \in B} x_r \\ &\text{s.t. } c_k x \geq g_k \quad \text{for } k = 0, 1, \ldots, n \\ &\quad A x \leq b \\ &\quad x \geq 0 \end{aligned} \tag{11}$$

where B is a set of the indices of the basic decision variables in the previous solution, and

g_k is the satisfactory level of objective k. By minimising the sum of basic decision variables in the previous solution, we obtain a solution that is maximally different from the previous one, while the constraints ensure that the generated solution is both satisfactory and feasible. The objective function value D is a measure of the difference between two solutions generated successively. If $D=0$, for example, then the newly generated solution is completely different from the previous one.

When this technique is used, an initial solution is needed to define the objective function of (11). An initial solution, that is satisfactory and easy to find, is the one corresponding to the satisfactory levels of the objectives. Given an initial solution x^0, the non-zero variables in x^0 form an objective function of (11). Solving this problem, we obtain a different solution x^1. On the basis of x^1, we form a new objective function, and generate a solution x^2 that is different from x^1. The process continues until a sufficient number of alternative solutions has been generated, or until no new solution can be found.

The optimisation problem corresponding to the second MGA technique is

$$\begin{aligned} &\max_x D = \sum_{r \in R} x_r \\ &\text{s.t. } c_k x \geq g_k \quad \text{for } k=0, 1, \ldots, n \\ &\qquad Ax \leq b \qquad\qquad\qquad\qquad\qquad (12) \\ &\qquad x \geq 0 \end{aligned}$$

where R is the set of a given number of randomly selected decision variable indices. Using this method, different solutions are generated by successively changing the objective function (*i.e.* the set R). With this model, however, the objective function value D in itself does not tell how different the generated solution is from the previous one.

Clearly, different alternatives can be generated only if the set of satisfactory solutions contains more than one feasible solution to the original MOLP problem. It should be pointed out that all solutions belonging to the satisfactory set in the objective space cannot be found by solving the optimisation problem (11) or (12). Therefore, when determining the satisfactory levels of the objectives, one must bear in mind that the point $(g_0, g_1, g_2, \ldots, g_n)$ should not be too close to the set of efficient solutions of the original MOLP problem. Otherwise, it is possible that only few, and quite similar, solutions can be generated.

In real applications, however, it is more likely that too many alternative solutions could be generated by use of the MGA techniques described above. If this is the case, the generating process must be stopped when a sufficient number of options has been obtained. It is then desirable to modify the MGA techniques so that one can control the generating process. For example, one may subjectively select the decision variables that enter the objective function, to generate a solution that differs from the previously generated solutions in certain respects.

Chang, Brill & Hopkins (1983) introduced a fuzzy approach to generating satisfactory and different alternatives. The LP formulation of the fuzzy generating model corresponding to the MGA model (11) is

$$\begin{aligned} &\max \lambda \\ &\text{s.t. } \lambda(D^u - D^l) + \sum_{r \in B} x_r \leq D^u \\ &\qquad -\lambda(g_k^u - g_k^l) + c_k x \geq g_k^l \quad \text{for } k=0, 1, \ldots, n \quad (13) \\ &\qquad Ax \leq b \\ &\qquad \lambda, x \geq 0 \end{aligned}$$

where B is a set of the indices of the basic decision variables in the previous solution, D^l and D^u are the lowest and highest acceptable values of the 'surrogate measure of difference' between the previous solution and the solution to be generated, and $g_k{}^l$ and $g_k{}^u$ ($k=0, 1, 2, \ldots, n$) are the satisfactory and target values of objective function k. Like the set B, the values of D^l and D^u should be modified each time a new solution is to be generated. By specifying an interval of acceptable values of the 'surrogate measure of difference', one can, to some extent, control how different the generated solutions will be.

A distinctive feature of this fuzzy MGA technique is that it automatically detects and chooses the most critical criterion in searching for different and satisfactory alternative solutions. The original MGA techniques distinguish between the 'satisfactory solutions', *i.e.* the feasible solutions of model (11) and (12), only in the decision space. These models implicitly assume that all of the 'satisfactory solutions' are equally satisfactory with respect to the modelled objectives, and generate solutions that are maximally different from each other in the decision space. In contrast, the fuzzy MGA technique distinguishes between the 'satisfactory solutions' not only in the decision space but also in the modelled objective space. Each of these solutions is evaluated in terms of level of satisfaction with respect to the modelled objectives, and in terms of the degree of difference in the decision space from the previously generated solution. Model (13) generates solutions by maximising the minimum of the two measures.

Like the basic MGA models, the fuzzy generating model (13) can be modified to enable more flexible generation of different and satisfactory solutions. Mendoza & Sprouse (1989), for example, introduced three options to the generating model (13). Unfortunately, we know very little about the set of 'satisfactory solutions' in the decision space and about the performance of different generating methods with respect to the solutions they could generate. It is therefore impossible to tell whether one method is better than another, in the sense that it can generate a better solution. Likewise, the fuzzy MGA technique, despite its conceptual advantage, is not clearly superior to the basic MGA methods.

The aim of applying MGA techniques is to generate a number of candidate solutions (management plans) from which the DM chooses one to implement. Because all the decision criteria are not clearly and precisely defined at this stage, the number of candidate solutions, as well how they are selected, may have a significant impact on the final choice of management plan. Previous applications of MGA techniques have focussed on the problem of unmodelled objectives or issues (Mendoza *et al.*, 1987; Campbell & Mendoza, 1988; Mendoza & Sprouse, 1989). Using the satisfactory values of the modelled objectives as constraints, one generates candidate solutions that are different in the decision space (and thus are likely to be different with respect to the unmodelled objectives). In this case, the set of generated candidate solutions depends, to a large extent, on the satisfactory levels of the modelled objectives.

It should be noted, however, that the satisfactory values of the modelled objectives are uncertain. The point is that whether or not an objective function value is satisfactory, depends on the values of the other objectives. A solution that is inferior with respect to the modelled objectives may be efficient (and thus can be chosen as a candidate solution) if it leads to a higher value of an unmodelled objective. An effective approach, taking into account the trade-offs between the satisfactory values of the modelled objectives, is to incorporate the idea of *de novo* programming into the MGA model. When the controllability of the generating process also is considered, the MGA model can be formulated as:

$$\max \sum_{r \in R} x_r - \sum_{i \in I} x_i$$

$$\text{s.t.} \sum_{k=0}^{n} w_k c_k x \geq z^0$$

$$Ax \leq b$$

$$x \geq 0$$

where R is the set of the favorable decision variables to be part of the generated solution, I is the set of decision variables to be excluded from the generated solution, w_k is the weight associated with modelled objective k, and z^0 is the aggregate satisfactory level of the modelled objectives. Conversion of this model to a fuzzy generating model is straightforward.

Determination of the optimal management plan

A number of methods can be used to search for the optimal management plan from a set of efficient or satisfactory options. However, the different methods are not entirely mutually consistent. Application of different methods to the same problem would usually not lead to the same conclusion as regards which management plan is optimal. There is no method that is universally superior to the others: each has its advantages and limitations. In what follows, we briefly discuss two methods: the analytical hierarchy process (AHP) and economic valuation.

The AHP is a well-established method of using a DM's subjective judgments to evaluate alternative choices in a multi-criteria decision problem. In general, application of the AHP method involves three steps. The first step is to develop a hierarchical presentation of the decision problem, which describes the components of the problem at different levels from the goal or overall objective down to the feasible decision alternatives. The second step is to construct matrices of pairwise comparisons of the components at each level of the hierarchy. To this end, one asks the DM to judge the importance of each component as compared with each of the other components at the same level, with respect to each component at the higher level. In the third step, the matrices of pair-wise comparisons are used to derive the relative weight of each decision alternative with respect to the overall objective of the decision problem. The optimal decision alternative is the one that has the greatest relative weight. See, *e.g.*, Kangas (1992) for a forestry application of the method.

Apparently, the AHP method can be applied to accomplish the second step in the bottom-up procedure of multiple-use forest planning. In this case, there is no need to go through all three steps of the AHP method. One need only ask the DM to make pairwise comparisons of different uses of the forest. These pairwise comparisons enable us to determine the relative weights of different uses, and thereby to determine the optimal management plan.

An attractive feature of the AHP method is that it is relatively simple. The DM may find it easier to make the necessary judgments, by needing to consider only two alternatives at a time. Moreover, the method provides a quantitative measure of the degree of consistency in the DM's judgments. In the context of multiple-use forest management, a main disadvantage of the AHP method relates to the difficulty of aggregating the judgments of different forest owners. When a forest is owned by a large number of individuals, conflicts among the forest owners will inevitably arise in the pairwise comparisons. One has to resolve the conflicts or aggregate the judgments of different individuals, to be able to choose a management plan by means of the AHP method.

Economic valuation of non-market-priced goods is a frequently applied approach to assessing individuals' preferences of non-timber uses of forests. An array of survey-based methods exists for measuring the willingness-to-pay (WTP) for a change in the provision of non-timber goods. Among these, the most commonly applied method is the contingent valuation (CV) method, which is based on the straightforward idea of asking people directly about their valuation of a change in the supply of the good in question (Ciriacy-Wantrup, 1947; Mitchell & Carson, 1989). The name 'contingent' valuation arises from the fact that the elicited value is contingent upon the scenario presented to the respondent in the survey (Field, 1994). An extension of the CV technique is to vary the attributes of the good in question, implying that the change in the non-timber good will involve more than one dimension. Varieties of this type of extension include, *e.g.*, choice experiments (CE), contingent ranking (CR), or conjoint analysis (CA) (Hanley *et al.*, 1998; Bergland, 1995). A common feature of CV, CE, CR and CA is that they all explicitly ask the respondent to state his or her preferences. These methods are therefore also known as stated preference methods. There is another category of economic valuation methods, known as revealed preference methods, which use observations on market transactions to estimate the underlying preferences for non-market-priced (*e.g.* non-timber) goods. Two well-known methods in this category are the travel cost method (Hanemann, 1992) and the hedonic pricing method (Griliches, 1971).

The valuation methods mentioned above enable us to quantify in monetary terms the DM's benefits from non-timber uses. Strictly speaking, these methods are not decision tools. However, use of the valuation results to determine the optimal forest management plan is straightforward. When the value of the non-timber uses associated with each management plan is known, it is easy to calculate the total net benefits, and to find the management plan that has the greatest total net benefits.

In addition to the methods mentioned above, there are other multiple-criteria, decision-making techniques that can be used to choose a multiple-use management plan from a finite number of options. See Howard (1990) for a review of the forestry applications of these techniques.

The interactive procedure

The interactive procedure is a process of alternate preference assessment and management-plan evaluation. Information about the DM's preferences is used to identify an efficient management plan, which is presented to the DM, and the feedback from the DM is used to identify another efficient management plan. An unique feature of the interactive procedure is that the

DM directly participates in the planning process. In the process, a sequence of efficient management plans is generated as the preferences of the DM are progressively defined. Note that a DM may give inconsistent information about preferences, upon the presentation of different management plans. This implies that the feedback from the DM does not always lead to more accurate description of the preferences, and thus not every iteration will generate a better management plan. For this reason, interactive techniques in general aim at finding a satisfactory management plan. If the DM is satisfied with the current management plan, the process stops. Otherwise, the DM is asked to answer certain questions designed to make a local estimate of his or her preferences. The information is used to find another efficient management plan, by reducing the search region, modifying the search criterion or both. In this section, we present two interactive planning techniques, the interactive NPV maximisation method and the STEM method. See Rustagi & Bare (1987), Steuer & Schuler (1978), and Liu & Davis (1995) for examples of applications of other interactive, multiple-objective forest planning techniques.

The interactive NPV maximisation method

Recall that a serious limitation of the NPV maximisation model (4), presented earlier in this section, is that one cannot find the optimal management plan without knowing the correct prices of non-timber goods (*i.e.* the prices of non-timber goods at the optimal output), while estimates of the correct prices can be obtained only when the optimal outputs of the non-timber goods are known. The management plan that maximises the NPV depends on the prices of non-timber goods, which in turn depend on the output of the non-timber goods and thus on the management plan. The relationship between the correct prices of the non-timber goods, p^e, and the optimal management plan can, in general, be described by the following equations:

$$p^e = p(g),\ g = f(x^*(p^e))$$

where $x^*(p^e)$ is the management plan that maximises the NPV given p^e, and g denotes the outputs of non-timber goods associated with management pan $x^*(p^e)$. This relationship has such a structure that one can successively approximate the correct prices of non-timber goods and the optimal management plan by iteration.

Consider the following simplified version of the NPV maximisation model (4).

$$\begin{aligned} &\max\ c_0 x + \sum_{k=1}^{n} p_k^e c_k x \\ &\text{s.t. } Ax \leq b \qquad\qquad (14) \\ &\quad x \geq 0 \end{aligned}$$

where c_0 is a vector of the NPV of timber production profits per unit area, c_k for $k = 1, 2, ..., n$ are a vector of the output of non-timber good k, and $p_k{}^e$ is the unit price of non-timber good k. This model specifies the dependence of the NPV maximising management plan on the prices of the non-timber goods. Successive approximation of the optimal management plan starts with an initial guess at the prices of the non-timber goods, denoted by $p^e(0)$. Each iteration involves two steps. The first step is to solve problem (14) by using $p^e(0)$ to generate an approximation of the optimal management plan x^0. The second step is to ask the DM for the maximum WTP for a marginal increase in the output of non-timber good k from the current level $c_k x^0$, for $k = 1, 2, ..., n$. The marginal WTPs provide a new vector of prices of the non-timber goods, denoted by $p^e(1)$. If $p^e(1) = p^e(0)$, then x^0 is the optimal management plan. Otherwise, let $p^e(0) = [p^e(0) + p^e(1)]/2$ and repeat the two steps. The process continues until it converges, *i.e.* until $p^e(1) = p^e(0)$.

This method requires that the DM provide information about the marginal WTPs in complete accordance with some utility function, because it is otherwise likely that the process will not converge. The sad fact is that empirically assessed WTPs almost always contain random errors. Owing to uncertainty in the DM's stated marginal WTPs, it is improper to determine when to stop the iteration process according to the convergence condition described above. First, it is not certain that the convergence condition will ever be satisfied. Secondly, even if the condition is by chance satisfied, it by no means implies that the current management plan is optimal.

Despite the uncertainty in WTPs, a sequence of efficient management plans can be generated by repeatedly assessing the DM's marginal

WTPs (conditional on the current output of the non-timber goods), and maximising the NPV (using the newly obtained information about the prices of the non-timber goods). If we change the solution criterion to 'stop if the DM is satisfied with the current management plan', then the interactive NPV maximisation method can be applied to real-world, multiple-use forest planning problems.

The step method (STEM)

The STEM generates a sequence of efficient management plans by minimising the maximum weighted distance to the ideal point. In the process, the weights assigned to different objectives, as well as the 'search region', are revised interactively, on the basis of the judgments of the DM. Given an efficient solution, the DM is asked to identify one objective, the value of which can be reduced, and to specify a tolerance level of the objective, in order to increase the value of the other objectives. The response from the DM is used to modify the weights associated with different objectives, and to define a new search region from which another efficient solution is identified. The process stops when a satisfactory solution is found or when no more improvements can be made. With reference to the MOLP formulation (9), the method can be described as follows.

Step 1. Solve the following single objective maximisation problem for $k=0, 1, 2, ..., n$

$$\max \ c_k x$$
$$\text{s.t. } Ax \leq b$$
$$x \geq 0$$

to determine the maximum and minimum values of each objective k, denoted by g_k^* and g_k^0 respectively, among the set of efficient solutions. Let $x^*(k)$, $k=0, 1, 2, ..., n$, be the optimal solution of the above problem when objective k is maximised. Then, the maximum value of objective k is $g_k^* = c_k x^*(k)$, and the minimum value of objective k is $g_k^0 = \min\ \{c_k x^*(0), c_k x^*(1), c_k x^*(2), ..., c_k x^*(n)\}$.

The ideal point is given by $(g_0^*, g_1^*, g_2^*, ..., g_n^*)$. The weights assigned to different objectives are calculated in the following way:

$$a_k = \frac{|g_k^* - g_k^0|}{|g_k^*|} \left[\sum_{j=1}^{m} (c_{kj})^2 \right]^{1/2}$$

where c_{kj} is the j-th element of the coefficient vector of objective function k.

Step 2. The weights associated with different objectives are normalised:

$$\lambda_k = a_k \left[\sum_{k=0}^{n} a_k \right]^{-1} \tag{15}$$

Given the normalised weights, one solves the following minimax problem to find an initial efficient solution that is closest to the ideal point:

$$\begin{aligned} &\min\ D \\ &\text{s.t. } \lambda_k(g_k^* - c_k x) \leq D \quad \text{for } k=0, 1, ..., n \\ &\quad Ax \leq b \\ &\quad x \geq 0 \end{aligned} \tag{16}$$

Denote the optimal solution of (16) by x^0. If the DM is satisfied with the solution x^0, then the process stops. Otherwise, the process continues with the following step.

Step 3. Given an efficient solution x^0 and the associated values of different objectives, the DM identifies one objective, the value of which can be reduced, and specifies a tolerance level of the objective (or an acceptable amount by which the objective can be reduced). Suppose that the value of objective l can be reduced from its current level by z_l. Set $\alpha_l=0$ and recalculate the normalised weights, λ_k for $k=0, 1, ..., n$, using Equation (15). Another efficient solution is obtained by solving the revised minimax problem.

$$\begin{aligned} &\min\ D \\ &\text{s.t. } \lambda_k(g_k^* - c_k x) \leq D \quad \text{for } k=0, 1, 2, ..., n \\ &\quad Ax \leq b \\ &\quad x \geq 0 \\ &\quad c_k x \geq c_k x^0 \quad \forall k \neq l \\ &\quad c_l x \geq c_l x^0 - z_l \end{aligned} \tag{17}$$

The last two constraints ensure that the generated solution is at least as good as the previous one with respect to all objectives except objective l; and the value of objective l cannot be smaller than its previous value by more than the specified amount z_l. Let x^1 be the optimal solution of problem (17). If the DM is satisfied with the solution x^1, the process stops. Otherwise, let $x^0 = x^1$ and repeat Step 3.

Note that, in each iteration, the weight of one objective is set to zero. Therefore, after a finite number of iterations there will be only one objective that has a weight greater than zero. It is then no longer possible to find additional efficient solutions by repeating the iteration step (Step 3), and the procedure must stop, even if the DM is still not satisfied with the current solution. Suppose that in each iteration the DM chooses an objective that has not been chosen before (*i.e.* an objective with a current weight greater than zero). The maximum number of effective iterations is then equal to the total number of objectives minus one. As an extreme example, if there are only two objectives, one can at most generate two efficient management plans using the STEM. The possibility of stopping the procedure without having found a satisfactory solution is a major drawback of the STEM (Cohon, 1978).

The advantage of the STEM is that it is easy to implement, and requires little information from the DM in the iterations. This property of the method makes it particularly suitable for analysing multiple-use forest planning problems, which often can be better described by including a large number of management objectives. Forest management plans are typically determined for long time horizons, divided into many time periods. Even if there is only one non-timber use of the forest – say recreation – it is better to describe the recreation capacity (or suitability) of the forest in each time period by a distinct objective, than to define a single objective relating to the recreation capacity over the entire planning horizon. This is because the recreation capacity in one period cannot be transferred to another period. It should be pointed out, however, that a larger number of objectives makes it more difficult for the DM to provide consistent feedbacks, and thereby increases the possibility of stopping the searching process arbitrarily.

How to choose among the planning procedures?

Having described the three procedures of multiple-use forest planning, a question that would naturally arise is which of the procedures should one use. The answer to this question depends on the characteristics of the forest planning problem at hand, and on the DM's knowledge about the problem. We cannot determine which procedure in general is most appropriate, since none of the procedures is universally superior to the others. Instead, we briefly discuss some important aspects of the planning procedures that should be considered when choosing among them.

A fundamental difference between these procedures lies in the amount of information about the multiple-use potentials and trade-offs provided to the DM before assessing his or her preferences. The top-down procedure does not provide such information to assist the DM in judging the relative importance of, or values of, different uses of the forest; the bottom-up procedure provides a description of the entire set of efficient multiple-use alternatives, whereas the interactive procedure provides information about a finite number of efficient options under the guidance of the DM. In principle, more information about the feasible management plans (in the objective space) can help the DM better describe his preferences which, in turn, makes it possible to find forest management plans closer to the most preferred one. In this respect, the bottom-up and the interactive procedures are preferable to the top-down procedure. On the other hand, it requires a considerable amount of analytical effort to describe (explore) the set of efficient management options. The top-down procedure is advisable when the DM has a good knowledge of his or her preferences and of the production potentials of the forest, because of the simplicity of implementing this procedure.

In many multiple-use forest planning situations, one has to examine the multiple-use potentials and trade-offs, in order to acquire reliable information about the DM's preferences; thus the bottom-up or interactive procedure should be used. Generally speaking, the bottom-up procedure generates a larger number of efficient options, while the interactive procedure requires inputs from the DM. The choice between these two procedures depends heavily on the number of management objectives and on the number of forest owners. When there are many management objectives, the bottom-up procedure requires a larger number of efficient management options to achieve a satisfactory description of the entire efficient set, which is a serious drawback. Moreover, it is difficult to present the tremendous amount of information in such a way that the DM is effectively assisted in specifying his or her preferences regarding the alternative uses of the forest. In such situations, it is advantageous to use the interactive approach. However, it should be pointed out that the performance of the interactive procedure depends on the number of forest owners. The procedure is most effective when there is a single forest owner. A larger number of forest owners makes it more difficult and costly to obtain accurate feedbacks from the forest owners.

An analyst cannot change the number of forest owners, but has some flexibility in modelling the management objectives. When the number of forest owners is large, *e.g.* in public forest management, it is difficult to apply the interactive procedure properly. The difficulty lies in that one must resolve the conflicts among individuals, to decide whether or not a management alternative is satisfactory. If there is one or a few forest owners, it may be proper to use either the bottom-up or the interactive procedure, although it would be desirable to formulate the planning model in different ways, depending on which procedure one chooses.

Limitations of multiple-use forest planning models

Optimisation models have been widely used in multiple-use forest planning. At the same time, applications of such models for identifying the optimal solution of the planning problem have been subject to criticism. The basis for the criticism is that an optimisation model is a simplification rather than a perfect representation of a real planning problem, and thus the optimal solution of the model may not be the optimal solution of the real problem. It should be pointed out that it is neither realistic nor rational to strive for an optimisation model that describes accurately the real planning problem in every detail (Cocklin, 1989a). The real problem is therefore not simplification in itself. Rather, it is that one cannot always make the simplifications rationally. Because of a lack of knowledge, and restrictions of optimisation techniques, some important aspects of the multiple-use forest planning problem often cannot be properly represented in the optimisation model. The major concerns relate to the aggregation of non-timber goods, interdependence among stands, and uncertainty.

A multiple-use, forest planning problem typically involves several non-timber goods and many decision periods. Aggregation of non-timber goods over time greatly reduces the number of attributes (as to the management outcomes) that should be recognised in the optimisation model. This helps to reduce the complexity of the optimisation model, and more importantly, the difficult task of assessing the DM's preferences among multiple-use forest management outcomes. Consideration of the total output of each non-timber good, however, imposes very restrictive assumptions on the DM's preferences (Gong, 1994). In reality, the possibility of reallocating the flow of non-timber goods over time for 'consumption' is limited, because of the lack of markets that facilitate borrowing and saving of the non-timber goods. Therefore, temporal variations in the outputs of non-timber goods affect the DM's preferences among the management alternatives. For example, a management alternative that results in an even flow of non-timber goods, may be preferable to one which has the same total outputs, but with large temporal variations. However, it is difficult properly to accommodate the impacts of the temporal variations in the optimisation model.

A serious problem of most multiple-use, forest planning models is that they do not fully account for interdependence among stands. It is widely recognised that the marginal value of non-timber goods from one stand is typically dependent on the output of non-timber goods from other stands. In addition to this value interdependence, there exist complex interactions among individual stands as to the output of non-timber goods. The quantity, quality, or both, of non-timber goods depends not only on the state of each of the stands in a forest, but also on the spatial distribution of the stands (*i.e.* spatial variations in stand states). While multiple-use, forest planning models recognise value interdependence among stands, the production relationships are usually assumed to be linear and the functional interactions among different stands therefore are ignored. Recent efforts have attempted to incorporate spatial concerns into forest planning models (*e.g.* Roise, 1990; Hof & Joyce, 1992, 1993; Murray, 1999). However, the approaches adopted to deal with the issue are *ad hoc*.

Uncertainty is another important aspect of multiple-use forest management problems that is difficult to accommodate in optimisation models. Although most forest planning models are deterministic, it is widely acknowledged that uncertainty exists both in the functional form and in the coefficients of the objective function and the constraints of a forest planning model. Essentially, most of the factors relevant to forest management decisions are uncertain. Uncertainty in these factors affects the set of feasible management alternatives, the outcomes associated with each feasible alternative, and the preferences of the DM. Several approaches, *e.g.* MGA (Mendoza *et al.*, 1987), fuzzy programming (Mendoza & Sprouse, 1989; Ells *et al.*, 1997), and the multi-objective, stochastic programming technique (demonstrated in Wang, 1991), have been proposed to recognise uncertainties involved in traditional forest planning models. These approaches implicitly assume that the DM's task is to determine a management plan, or rather a course of action, for the whole planning horizon. However, the rationale of determining an optimal course of action for the whole planning horizon can be questioned. Since the market conditions and forest states in each future period are uncertain, it is reasonable for the DM to determine what to do in each period, conditional on the realised economic and biological conditions in that period, implying that the optimal management activity in a future period is uncertain. Multi-objective stochastic dynamic programming is, in principle, a suitable approach for modelling the adaptive decision process under conditions of uncertainty (see *e.g.* De Kluyver *et al.*, 1980; and Gong, 1992 for example applications). However, practical applications of this approach are restricted because of the dimensionality problem.

Concluding remarks

Applications of optimisation techniques in general, and multi-objective programming in particular, in multiple-use forest planning have been extensively studied. The great complexity of multiple-use forest planning problems makes optimisation techniques especially attractive. On the other hand, it usually requires significant simplification of a real problem to be able to formulate a manageable optimisation model, and for this reason, the use of the model for identifying the optimal solution of the problem has been questioned. Recent developments in programming methodology have, to some extent, allowed for more realistic descriptions of multiple-use forest planning problems. However, it is rarely the case that a planning problem can be adequately represented by an optimisation model. There are important aspects of multiple-use forest planning problems that cannot be appropriately incorporated into a model. The limitations of forest planning models are not necessarily the results of the restrictions of optimisation techniques, as was sometimes argued. Rather, the difficulties in specifying adequate multiple-use forest planning models arise from the inherent complexity of the planning problems, and from the lack of sufficiently precise information about the preferences of the DM and about the production relationships. These difficulties exist irrespective of which analytical tool one uses. Therefore, it is doubtful whether developments in optimisation methodology would enable us to overcome the difficulties encountered in multiple-use forest planning.

Despite these concerns, optimisation techniques still have an important part to play in multiple-use forest planning, and can hardly be replaced by other methods. The complexity of the problems, and the lack of sufficient information, have motivated the investment of great research effort into the exploration of alternative approaches to multiple-use forest planning. There is a variety of methodologies, such as non-market valuation methods and multi-criteria decision-making techniques, that can contribute to multiple-use forest planning, but each has its limitations. This situation calls for creative use of models and optimisation techniques. First of all, models should be formulated to serve as a tool for integrating optimisation techniques and alternative evaluation/decision-making methods. When formulating the models, one should pay particular attention to the full implications of the lack of markets for non-timber goods, and to the differences in quantity and quality of information about different aspects of multiple-use planning problems. Secondly, optimisation results should be viewed as a partial evaluation of the multiple-use management alternatives. When making the final choice of management alternative, the DM should take into account those issues he or she perceives as important, but which were not incorporated into the optimisation models.

In the past decade, the concept of ecosystem management has received considerable attention, as a result of increasing concerns about the sustainability of forest resources and forestry. The focus of ecosystem management is the preservation of biodiversity and productivity of forest ecosystems. Thus ecosystem management is in a sense a tool for ensuring that various benefits from the forest and its management can be sustained. Another way of looking at it is that ecosystem management imposes an additional objective, namely the preservation of biodiversity and productivity, on multiple-use forest management. While the concept embodies a new management philosophy, it does not suggest any apparently better substitutes for the multiple-use forest planning techniques. A rigorous analysis of the ecosystem management problem requires knowledge about the functioning and dynamics of forest ecosystems. Given this knowledge, multiple-use forest planning techniques can be readily applied to examine the optimum balances between the outputs of timber and non-timber goods and the degree or extent of sustainability, which is the key analytical issue in ecosystem management.

References

Allen, J.C. 1986. Multiobjective regional forest planning using the noninferior set estimation (NISE) method in Tanzania and the United States. *Forest Science 32*, 517–533.

Arp, P.A. & Lavigne, D.R. 1982. Planning with goal programming: a case study for multiple use of forest land. *Forestry Chronicle* 58, 225–232.

Bare, B.B. & Mendoza, G.A. 1988. A soft optimization approach to forest and management planning. *Canadian Journal of Forest Research 18*, 545–552.

Bare, B.B. & Mendoza, G.A. 1990. Designing forest plans with conflicting objectives using *de Novo* programming. *Journal of Environmental Management 31*, 237–246.

Bare, B.B. & Mendoza, G.A. 1992. Timber harvest scheduling in a fuzzy decision environment. *Canadian Journal of Forest Research 22*, 423.-428.

Bergland, O. 1995. *Valuing multidimensional environmental changes with contingent ranking*. Agricultural University of Norway, Department of Economics and Social Sciences, Discussion Paper, Ås.

Binkley, C.S. 1987. When is the optimal economic rotation longer than the rotation of maximum sustained yield? *Journal Environmental Economics and Management 14*, 152.-158.

Bowes, M.D. & Krutilla, J.V. 1985. Multiple use management of public forestlands. In: *Handbook of natural resource and energy economics,* Vol. II. Kneese, A.V. & Sweeney, J.L. (eds.), North Holland, Amsterdam. pp. 531–569.

Bowes, M.D. & Krutilla, J.V. 1989. *Multiple-use management: the economics of public forestlands.* Resource for the Future, Washington, DC.

Brill, E.D., Chang, S.Y. & Hopkins, L.D. 1982. Modeling to generate alternatives: The HSJ approach and an illustration using a problem in land use planning. *Management Science 28*, 221–235.

Calish, S., Fight, R.D. & Teeguarden, D.E. 1978. How do nontimber values affect Douglas-fir rotations? *Journal of Forestry 76*, 217–221.

Campbell, G.E. & Mendoza, G.A. 1988. Adapting modeling to generate alternatives (MGA) techniques to forest level planning. *Journal of Environmental Management 26*, 151–161.

Chang, S.J. & Buongiorno, J. 1981. A programming model for multiple use forestry. *Journal of Environmental Management 13*, 41–54.

Chang, S.Y., Brill, E.D. & Hopkins, L.D. 1982. Efficient random generation of feasible alternatives: a land use example. *Journal of Regional Science 22*, 303–314.

Chang, S.Y., Brill, E.D. & Hopkins, L.D. 1983. Modeling to generate alternatives: a fuzzy approach. *Fuzzy sets and Systems 9*, 137–151.

Charnes, A. & Cooper, W.W. 1963. Deterministic equivalents for optimizing and satisfying under chance constraints. *Operations Research 11*, 18–39.

Ciriacy-Wantrup, S.V. 1947. Capital returns from soil-conservation practices. *Journal of Farm Economics 29*, 1188–1190.

Clawson, M. 1974. Conflicts, strategies, and possibilities for consensus in forest land use and management. In: *Forest Policy for the Future*. Resource For The Future, Working Paper LW-1.

Cocklin, C. 1989a. Mathematical programming and resources planning I: the limitations of traditional optimization. *Journal of Environmental Management 28*, 127–141.

Cocklin, C. 1989b. Mathematical programming and resources planning II: new developments in methedology. *Journal of Environmental Management 28,* 143–156.

Cohon, J.L. 1978. *Multiobjective programming and planning*. Academic Press. 333 pp.

Dana, S.T. 1943. Multiple use, biology, and economics. *Journal of Forestry 41*, 625–626, De Kluyver, C.A., Daellenbach, H.G. & Whyte, A.G.D. 1980. A two-stage multiple objective mathematical programming approach to optimal thinning and harvesting. *Forest Science 26*, 674–686.

Dyer, A.A., Hof, J.G., Kelly, J.W., Crim, S.A. & Alward, G.S. 1979. Implications of goal programming in forest resources allocation. *Forest Science 25*, 535–543.

Ells, A., Bulte, E. & van Kooten, G.C. 1997. Uncertainty and forest land use allocation in British Columbia: Vague priorities and imprecise coefficients. *Forest Science 43*, 509–520.

Englin, J. 1990. Backcountry hiking and optimal timber rotation. *Journal of Environmental Management 31*, 97–105.

Field, B.C. 1994. *Environmental economics: an introduction*. McGraw-Hill, Inc, New York.

Field, D.B. 1973. Goal programming for forest management. *Forest Science 19*, 125–135.

Field, R.C. 1978. Timber management planning with Timber RAM and goal programming. *USDA Forest Service, General Technical Report, PSW-32*.

Flick, W.A. 1976. An input-output model of public forest management. *Canadian Journal of Forest Research 6*, 170–178.

Freeman, A.M. 1993. *The measurement of environmental and resource values: Theory and methods*. Resources for the Future, Washington, D.C.

Gong, P. 1992. Multiobjective dynamic programming for forest resource management. *Forest Ecology and Management 48*, 43–54.

Gong, P. 1994. Forest management decision analysis. *Swedish University of Agricultural Sciences, Department of Forest Economics, Report 105*. ISSN 0348-2049. 131 pp.

Gong, P. & Kriström, B. 1999. Regulating forest rotation to increase CO_2 sequestration. *Swedish University of Agricultural Sciences, Department of Forest Economics, Working paper 272*.

Gregory, G.R. 1955. An economic approach to multiple-use. *Forest Science 1*, 6–13.

Gregory, G.R. 1987. *Resource economics for foresters* (2nd ed.). John Wiley & sons, New York.

Griliches, Z. (ed.). 1971. *Price indexes and quality change*. Harvard University Press, Cambridge, Massachusetts.

Hanemann, W.M. 1992. Preface. In: *Pricing the European environment*, Navrud, S. (ed.), Scandinavian University Press, Oslo. pp. 9–35.

Hanley, N., Wright, R.E., & Adamowicz, V. 1998. Using choice experiments to value the environment. *Environmental and Resource Economics 11*, 413–428.

Hartman, R. 1976. The harvesting decision when a standing forest has value. *Economic Inquiry 14*, 52–58.

Hite, M., Johansson, P.O. & Löfgren, K.G. 1987. On optimal rotations when a standing forest has value. *Swedish University of Agricultural Sciences, Department of Forest Economics, Report 70*. ISSN 0348-2049. 15 pp.

Hof, J.G. & Joyce, L.A. 1992. Spatial optimization for wildlife and timber in managed forest ecosystems. *Forest Science 38*, 489–508.

Hof, J.G. & Joyce, L.A. 1993. A mixed integer linear programming approach for spatially optimizing wildlife and timber in managed forest ecosystems. *Forest Science 39*, 816–834.

Hof, J.G. & Pickens, J.B. 1991. Chance-constrained and chance-maximizing mathematical programs in renewable resource management. *Forest Science 37*, 308–325.

Hotvedt, J.E., Leuschner, W.A. & Buyhoff, G.J. 1982. A heuristic weight determination procedure for goal programs for harvest scheduling. *Canadian Journal of Forest Research 12*, 292–298.

Howard, A.F. 1991. A critical look at multiple criteria decision making techniques with reference to forestry applications. *Canadian Journal of Forest Research 21*, 1649–1659.

Hyberg, B.T. 1987. Multiattribute decision theory and forest management: a discussion and application. *Forest Science 33*, 835–845.

Johansson, P.O. & Löfgren, K.G. 1985. *The economics of forestry and natural resources*. Basil Blackwell, Oxford. 292 pp.

Johansson, P.O., Löfgren, K.G. & Mäler, K.G. 1989. Multiple use, Pareto optimality and timber supply. In: *Multiple use of forests–economics and policy*, Mattsson, L. & Sodal, D.P. (eds.), Scandinavian Forest Economics, No. 31. pp. 106–125.

Kangas, J. 1992. Multiple-use planning of forest resources by using the analytical hierarchy process. *Scandinavian Journal of Forest Research 7*, 259–268.

Kuuluvainen, J. & Tahvonen, O. 1999. Testing the forest rotation model: evidence from panel data. *Forest Science 45*, 539–551.

Leuschner, W.A. 1990. *Forest regulation, harvest scheduling, and planning techniques*. John Wiley & sons, New York. 281 pp.

Leuschner, W.A., Porter, J.R. Reynolds, M.R. & Burkhart, H.E. 1975. A linear programming model for multiple-use planning. *Canadian Journal of Forest Research 5*, 485–491.

Liu, G. & Davis, L.S. 1995. Interactive resolution of multiobjective forest planning problems with shadow price and parametric analysis. *Forest Science 41*, 452–469.

Mattsson, L. 1990. Moose management and the economic value of hunting: towards bioeconomic analysis. *Scandinavian Journal of Forest Research 5*, 575–581.

Mattsson, L. & Li, C.Z. 1994. How do different forest management practices affect the nontimber value of forests? an economic analysis. *Journal of Environmental Management 41*, 79–88.

Mendoza, G.A. 1986. A heuristic programming approach in estimating target levels in goal programming. *Canadian Journal of Forest Research 16*, 363–366.

Mendoza, G.A. 1987. Goal programming formulations and extensions: An overview and analysis. *Canadian Journal of Forest Research 17*, 575–581.

Mendoza, G.A., Bare, B.B. & Campbell, G.E. 1987. Multiobjective programming for generating alternatives: a multiple-use planning example. *Forest Science* 33, 458–468.
Mendoza, G.A., Bare, B.B. & Zhou, Z. 1993. A fuzzy multiple objective linear programming approach to forest planning under uncertainty. *Agricultural Systems 41*, 257–274.
Mendoza, G.A. & Sprouse, W. 1989. Forest planning and decision making under fuzzy environments: an overview and illustration. *Forest Science 35*, 481–502.
Mitchell, R.C. & Carson, R.T. 1989. *Using surveys to value public goods: the contingent valuation method.* Resources for the Future, Washington D.C. ISBN 0-915 707-32-2. 463pp.
Murray, A.T. 1999. Spatial restrictions in harvest scheduling. *Forest Science 45*, 45–52.
Nguyen, D. 1979. Environmental services and the optimum rotation problem in forest management. *Journal of Environmental Economics and Management 8*, 127–136.
Pearson, G.A. 1944. Multiple use in forestry. *Journal of Forestry 42*, 243-249.
Raiffa, H. 1968. *Decision analysis.* Addison-Wesley, Reading, MA. 309 pp.
Roise, J.P. 1990. Multicriteria nonlinear programming for optimal spatial allocation of stands. *Forest Science 36*, 487–501.
Rustagi, K.P. & Bare, B.B 1987. Resolving multiple goal conflicts with interactive goal programming. *Canadian Journal of Forest Research 17*, 1401-1407.
Schuler, A.T., Webster, H.H. & Meadows, J.C. 1977. Goal programming in forest management. *Journal of Forestry 75*, 320–324.
Smith, V.K. 1998. Pricing what is priceless: a status report on non-market valuation of environmental resources. In: *The international yearbook of environmental and resource economics 1997/1998: a survey of current issues.* Folmer, K. & Tietenberg, T. (eds.), Edward Elgar, Cheltenham. pp. 156–204.
Snyder, D.L. & Bhattacharyya, R.N. 1990. A more general dynamic economic model of the optimal rotation of multiple-use forests. *Journal of Environmental Economics and Management 18*, 168–175.
Steuer, R.E. 1976. Multiple objective linear programming with interval criterion weights. *Management Science 23*, 305–316.
Steuer, R.E. & Schuler, A.T. 1978. An interactive multiple objective linear programming approach to a problem in forest management. *Operations Research 26*, 254–269.
Swallow, S.K. & Wear, D.N. 1993. Spatial interactions in multiple-use forestry and substitution and wealth effects for the single stand. *Journal of Environmental Economics and Management 25*, 103–120.
Tarp, P. & Helles, F. 1995. Multicriteria decision making in forest management planning – an overview. *Journal of Forest Economics 1*, 273–306.
van Kooten, G.C., Binkley, C.S. & Delcourt, G. 1995. Effect of carbon taxes and subsidies on optimal forest rotation age and supply of carbon services. *American Journal of Agricultural Economics 77*, 365–374.
von Neumann, J. & Morgenstern, O. 1947. *Theory of games and economic behavior.* 2nd Ed. Princeton University Press, Princeton, NJ. 641 pp.
Walker, H.D. 1985. An alternative approach to goal programming. *Canadian Journal of Forest Research 15*, 319–325.
Wang, D.H. 1991. The application of multiobjective stochastic programming approach to forest management planning. *Quarterly Journal of Chinese Forestry 24*, 3–31.
Zeleny, M. 1974. *Linear multiobjective programming.* Springer-Verlag, New York. 220 pp.

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