ABSTRACT. Recently, increasing weight has been placed on nontimber values in forest management. Both the multiple objectives and the parameters that support decision making in forestry are often imprecise and vague. In this paper, the concepts of fuzzy set theory are explained and then applied to the problem of allocating public forestland on Vancouver Island among competing land uses. Two principal sources of fuzziness are identified—those related to uncertainty in classification (specification of management objectives) and those related to uncertainty concerning how actions affect objectives (imprecise technical coefficients). By comparing the results of classical and fuzzy decision models, we conclude that the latter approach can be judged an improvement over the former. The fuzzy land-use allocation appears to be more consistent with the political decision making process, which relies on consultation and consensus-seeking among various interest groups, that has evolved in British Columbia. The analysis also yields insights into the robustness of outcomes and suggests priority areas for further research. For. Sci. 43(4):509–520.

Additional Key Words: Multiple-objective management, fuzzy set theory, uncertainty.

The Government of British Columbia in Canada owns more than 95% of the forestland in the province. In the past, these lands had been managed primarily for production of commercial timber from mature stands. During the late 1970s and 1980s, replanting of denuded, not sufficiently restocked forestlands took precedence over other environmental concerns, but during the early 1990s the Government introduced several initiatives to address additional environmental objectives. These initiatives included a Protected Areas Strategy (PAS), Timber Supply Reviews, the Commission on Resources and Environment (CORE) process, a Forest Practices Code, a Forest Renewal Plan, and a Forest Land Reserve (see van Kooten 1995). The policies reflect growing public recognition that forests are more than a source of industrial output. While the importance of commercial timber production to the provincial economy is not in doubt, managing land for multiple uses requires trading off different objectives in forest land management. In this paper, we examine a particular aspect of land management, namely that of allocating forestland under uncertainty using a zoning instrument. To address uncertainty, we employ fuzzy set theory.

Allocation of forestlands, including protected areas, has defaulted to the CORE, which is charged with finding consensus among various stakeholder groups. The philosophy that emerged during the CORE process was to treat each of the multiple objectives of land use as equally important, so that economic efficiency was not given preeminent status. Under this condition, traditional multiple objective decision making (MODM) is the most appropriate tool of analysis. The usefulness of classical MODM models is limited, however, because of the following characteristics inherent in the land use decision-making process:

- the objectives of society are ill-defined;
- the values that society attaches to various forest activities (such as recreation or preservation of biodiversity) are imprecise at best, or simply unknown;
- the effects of silviculture and other forest management decisions are uncertain, both from a biological and socio-economic perspective;
- land use and silvicultural decisions often pertain to an uncertain and distant future; and
- there is uncertainty about forest tenures, the macro economy, future product prices, and the ability of, or need for, governments to reduce deficits/debts.

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In this paper, we address uncertainty. Uncertainty has to do with the degree of belief or faith in the validity of a particular proposition or datum (Kruse et al. 1991). It arises from many sources, including measurement error, lack of judgement, imprecision, unreliability, variability, vagueness, ignorance, and ambiguity. The theory of fuzzy sets is used in this study to deal with vagueness. Vagueness is said to occur when an object is known completely but its classification is in doubt because the set to which it may belong is defined poorly (Barrett and Pattanik 1989); vagueness refers to the lack of clearcut boundaries for the set of objects to which the symbol or meaning is applied (Fedrizzi 1987). Vagueness is related to imprecision (Cox 1994, p. 608).

Applications of fuzzy set theory in the field of forestry and land-use planning are expanding. Mendoza and Sprouse (1989) proposed a two-stage approach to forest planning and developed a fuzzy model for more flexible and robust generation of alternatives. The uncertainty in their model arose from imprecise coefficients and was modeled by tolerating some constraint violations. Hof et al. (1986), Pickens and Hof (1991), and Bare and Mendoza (1992) compared classical (i.e., crisp) and fuzzy models for describing optimal harvest over time. They found that, by relaxing the constraint of nondeclining harvest volume over time, net present value (NPV) could be significantly increased (see also Hof 1993, p. 103–114). Mendoza et al. (1993) developed a fuzzy multiple objective linear programming model for forest planning that accommodated uncertainty in the objective function by making coefficients interval-valued. Finally, Tecle et al. (1994) developed an interactive fuzzy multicriterion decision model in which the decision maker is allowed to search the frontier of efficient solutions instead of being confronted with a uniquely preferred solution. Fuzzy set theory was used to deal with a vague objective and constraint.

This paper differs from previous ones because its scope is broader. In Bare and Mendoza (1992) and Pickens and Hof (1991), for instance, the focus is on timber yield only. We have a social orientation in which timber is but one of many services provided by forests. Obviously, extending the analysis to allow for recreation and preservation benefits requires data that are less precise than similar data for timber, because they are unobservable in markets and are difficult to measure. While Bare and Mendoza (1992) argue that imprecise (timber) coefficients are better viewed as stochastic rather than fuzzy, in this paper we address imprecision in coefficients as fuzzy measures.

The broader scope also implies that the impact of fuzzifying a crisp model is different. If fuzzifying simply amounts to relaxing a constraint of a NPV maximization model, then the predictable result is that NPV will increase! Relaxing a binding constraint will always have this effect. In our analysis, fuzziness actually affects the allocation of land among uses; this is a less than trivial result of the fuzzy approach.

Finally, this is the first paper in the field that actually combines the existence of vague objectives and constraints, as in Tecle et al. (1994) and Pickens and Hof (1991), and imprecise coefficients, as in Mendoza and Sprouse (1989), Bare and Mendoza (1992), Hof et al. (1995) and Mendoza et al. (1993). Moreover, imprecise coefficients are dealt with explicitly by modeling them as fuzzy numbers instead of incorporating them implicitly in the analysis as admissible violations of constraints, as in Mendoza et al. (1993). The approach taken in this paper gives more insight into the effect of the various sources of uncertainty on land allocation and makes better use of available information.

The purpose of the current research is to capture the uncertainty inherent in describing the socioeconomic impacts of land use and forest management decisions on Vancouver Island. The major objectives of this study are threefold: (1) to develop a fuzzy multiple objective decision-making model that incorporates uncertainties both in objective specification and parameter values; (2) to contrast the fuzzy models to a classical multiple objective approach where uncertainty is not considered; and (3) to demonstrate the usefulness of fuzzy set theory in the context of a multiple objective decision-making model for land use on Vancouver Island. Vancouver Island was selected because it is a region where land use conflicts are intense, and the recent CORE (1994) land use recommendations (subsequently adopted by government) have been controversial.

The rest of the paper is organized as follows. In section 2, we provide a brief, formal description of fuzzy logic, followed by the development of three fuzzy decision support models. The derivation of the required parameters for the models is presented in section 3, while the empirical results are provided in section 4. Our conclusions ensue.

Uncertainty and Fuzzy Set Theory

Current literature concerned with modeling uncertainty provides a wide range of definitions both for the concept of uncertainty itself as well as the various types of uncertainty that may be addressed (see, e.g., Krawize and Clark 1993, Kruse et al. 1991). In this regard, fuzzy set theory has become a particularly fruitful line of research for dealing with vagueness and ambiguity (e.g., Cox 1994, Zimmerman 1991, Barret and Pattanik 1989, Fedrizzi 1987). Dubois and Prade (1993) and Kosko (1992, p. 264–268) have shown that there is a clear distinction between probability theory and fuzzy set theory—that the fuzzy approach to uncertainty is valid in its own right, and that it is different from the Bayesian approach of probability theory.

In this section, we provide a formal treatment of fuzzy logic by considering membership or indicator functions for fuzzy sets (objective targets) and fuzzy numbers for imprecise values of the technical coefficients in the decision model. This background constitutes the formal foundation for the fuzzy MODMs, without and with imprecise coefficients, that are developed in the next section.

Fuzzy Sets and Membership Functions

An element $x$ of the universal set $X$ is assigned to an ordinary (crisp) set $A$ via the characteristic function $\mu_A$, such that:

---

1 The papers by Mendoza et al. (1993) and Tecle et al. (1994) deal with multiple objectives, but are based on NPV maximization models.
\( g_A(X) = 0 \) otherwise (1)

The element has either full membership \((g_A(x) = 1)\) or no membership \((g_A(x) = 0)\) in the set \(A\). The valuation set for the function is the pair of points \([0,1]\). A fuzzy set \(A\) is also described by a characteristic function, the difference being that the function now maps over the closed interval \([0,1]\).

Formally, a fuzzy set of \(X\) is defined by its membership function

\[ g: X \rightarrow [0,1] \] (2)

which assigns to each element \(x \in A \subseteq X\) a real number \(g_A(x)\) in the interval \([0,1]\), representing the grade or degree of membership of \(x\) in \(A\) (Sakawa 1993). While membership functions can take on a variety of functional forms, linear specifications are often employed.

An example of fuzzy membership is the set of “natural forests,” where it is clear that old-growth forests belong to this set with a degree of membership equal to one. As we consider progressively heavier logged forests, the descriptor “natural” becomes less apt. Partly logged forests are assigned a partial degree of membership in the set “natural forests,” something less than one. This is an example of a one-sided fuzzy set, with membership in the set approaching zero as the exploitation pressure increases. A twosided fuzzy set might be the set of “ponds.” A “pond” ceases to be one when it becomes so large that it is better conceived of as a “lake,” or when it becomes so small that it is better thought of as a “puddle.” It is the researcher’s task in these cases to construct the relevant fuzzy sets for the sets “natural forests” or “ponds.”

The preceding definitions of membership employed the concept of a normalized fuzzy set. A fuzzy set \(A\), defined over a finite interval, is said to be normal if there exists an \(x \in X\) such that \(g_A(x) = 1\), and 0 \(\leq g_A(x) \leq 1\ \forall x \in X\). A subnormal fuzzy set is normalized by dividing \(g_A(x)\) by its height or greatest membership value.

Set theoretic operations are defined for fuzzy sets. Among these are the concepts of containment, complement, intersection, and union. Fuzzy set \(\tilde{A}\) is a subset of \(B\) if and only if the membership function of \(\tilde{A}\) is less than or equal to that of \(B\) everywhere on \(X\):

\[ \tilde{A} \subseteq B \iff \mu_{\tilde{A}}(x) \leq \mu_B(x) \text{ for all } x \in X \] (3)

The complement of \(\tilde{A}\) (written as \(\tilde{A}\)) is defined as:

\[ \mu_{\tilde{A}}(x) = 1 - \mu_A(x) \] (4)

Hence, the intersection \(\tilde{A} \cap \tilde{B}\) is the largest fuzzy set contained in both \(\tilde{A}\) and \(\tilde{B}\), and the union \(\tilde{A} \cup \tilde{B}\) is the smallest fuzzy set containing both \(\tilde{A}\) and \(\tilde{B}\).

While both union and intersection of fuzzy sets are commutative, associative, and distributive, as is the case for ordinary or crisp sets, fuzzy logic deviates from crisp logic because, if we do not know \(\tilde{A}\) with certainty, then its complement \(\tilde{A}\) is also not known with certainty. Thus, \(\tilde{A} \cap \tilde{A}\) does not produce the null set as is the case for crisp sets (where \(A^c \cap A = \emptyset\)). Thus, fuzzy logic violates the “law of noncontradiction.” It also violates the “law of the excluded middle” because the union of a fuzzy set and its complement does not equal the universe of discourse—the universal set \(X\). Thus, \(\tilde{A}\) is properly fuzzy iff \(\tilde{A} \cap \tilde{A} \neq \emptyset\) and \(\tilde{A} \cup \tilde{A} \neq X\) (Kosko 1992, p. 269-272).

**Fuzzy Numbers and Alpha Cuts**

A fuzzy number describes the situation where a parameter value is “approximately \(m\)” or “about \(n\).” Fuzzy numbers are approximations of a central value and can be represented by “bell” curves, triangular functions, trapezoids, and so on (Cox 1994). A standard form of fuzzy number that allows for computational efficiency is that of the linear L-R (left-right) fuzzy number. A fuzzy L-R number \(M\) is fully characterized by three parameters—\(m\) is the central value of \(M\) and \(\sigma, \beta\) are the left and right spreads, respectively. It is defined as:

\[ \mu_M(x) = \begin{cases} \frac{m-x}{\sigma} & x \leq m, \sigma > 0 \\ \frac{x-m}{\beta} & x \geq m, \beta > 0 \end{cases} \] (7)

\(L\) and \(R\) as \((m, \sigma, \beta)_{LR}\). Operations for fuzzy numbers of the L-R type have been provided by Sakawa (1993, p. 26-30). Given the fuzzy numbers \(M = (m, \sigma, \beta)_{LR}\) and \(N = (n, \gamma, \delta)_{LR}\), the basic L-R fuzzy operators for symmetric fuzzy numbers (where \(\beta = \sigma = \gamma = \delta\)), are as follows:

**Addition:** \((m, \beta)_{Sym} \oplus (n, \gamma)_{Sym} = (m+n, \beta+\gamma)_{Sym}\) (8)

**Subtraction:** \((m, \beta)_{Sym} \ominus (n, \gamma)_{Sym} = (m-n, \beta+\gamma)\) (9)

**Multiplication:** \((m, \beta)_{Sym} \odot (n, \gamma)_{Sym} = (mn, n\beta + m\gamma)_{Sym}\ \text{iff } m, n > 0\) (10)

**Scalar multiplication:** \(k \otimes (m, \beta)_{Sym} = (km, k\beta)_{Sym}\) (11)

---

2 The characteristic function should not be confused with probability. Probability deals with the quantification of an uncertain event, while fuzzy set theory deals with the quantification of the uncertainty of the description of the event (see Kosko 1992).
The fuzzy number $M = (m, \beta)_{Sym}$ resembles a membership function in appearance and is used to describe a continuous quantity distribution about an imprecise parameter. While $m$ is the central value of the fuzzy number $M$, the width of the spread defined for the set is an indication of the reliability of the estimate. Typically, narrow spreads correspond with reliable estimates for the imprecise parameter.

Although fuzzy numbers assume symmetry, this does not presuppose symmetry in solution sets. The response in any one parameter value to a change in the fuzzy quantity is strictly a function of the spread ($\beta$) defined for that number. The spread defines the slope of the linear possibility distribution completely and thus the rate of change in value. It is the net result of all such independent movements that determines the ultimate solution.

Another concept required for model building with fuzzy sets is that of the $\alpha$-level set. The $\alpha$-level set $A_\alpha$ is simply that subset of $\tilde{A}$ for which the degree of membership exceeds the level $\alpha$, and is itself a crisp set (an element either meets the required level of $\alpha$ or it does not).

$$A_\alpha = \{ x | \mu_{\tilde{A}}(x) \geq \alpha \}, \alpha \in [0,1]$$  \hspace{1cm} (12)

$A_\alpha$ is an upper level set of $\tilde{A}$. The use of $\alpha$-level sets provides a means of transferring information from a fuzzy set into a crisp form. Defining an $\alpha$-level set is referred to as taking an $\alpha$-cut, cutting off that portion of the fuzzy set whose members do not have the required membership. Taking different $\alpha$-cuts allows the decision maker to consider different “realizations” of the problem, based on how much uncertainty he or she wishes to consider.\footnote{If an $\alpha$-cut is taken for several coefficients individually, then the overall output confidence associated with this $\alpha$-cut is unknown. If the decision maker is more concerned with total output uncertainty than with uncertainty levels in individual model coefficients, this may be an important omission. We thank John Hof for pointing this out to us.}

A fuzzy model with vague preferences and imprecise coefficients can be formulated as a crisp linear program (LP), as illustrated in this section. We acknowledge that classical formulations exist that closely resemble the fuzzy model developed here—the class of “minimum distance models” bears some resemblance. However, the setup of the problem would be different, and so is its conceptualization in the context of uncertainty.

**Fuzzy Multiple Objective Linear Programming**

In the fuzzy MODM model, we are concerned with uncertainty surrounding the definition of satisfactory solution values for each of the objective functions. Although a precise value for each objective is provided by the model, it is unclear as to how well that value represents the concept of a fully satisfied objective. The term “satisfactory solution” is defined vaguely; it is a fuzzy set. Thus, a goal $G(x)$ or constraint $C(x)$ may be completely satisfied by the choice of the solution vector $x$ ($\mu_G(x) = 1$ or $\mu_C(x) = 1$, completely unsatisfied ($\mu_G(x) = 0$ or $\mu_C(x) = 0$), or somewhat satisfied ($0 < \mu_G(x), \mu_C(x) < 1$). Crisp goals and constraints are accommodated in this framework by defining a crisp set as a specialized case of a fuzzy set.

The decision space, $\mu_D$, is the fuzzy set defined by the intersection of the fuzzy goal and the fuzzy constraint, and is characterized as

$$\mu_D(x) = \min(\mu_G(x), \mu_C(x))$$  \hspace{1cm} (13)

The decision space is illustrated in Figure 1.

It follows that, in order to maximize the minimum degree of satisfaction of the goals and constraints, the objective function for the fuzzy linear programming model is:

$$\max \mu_D(x) = \max \min (\mu_G(x), \mu_C(x)), \ x \in X$$  \hspace{1cm} (14)

This maxmin operator is but one of several ways to represent the decision. In the absence of evidence for ranking operators, maxmin was chosen because it is simple and linear, but it may fail to capture the true decision making process. Use of the maxmin operator removes the necessity of explicitly assigning weights or rankings to the goals and constraints—none are favored over any of the others in terms of determining the optimal solution. However, implicit weightings are assigned by the choice of parameters describing the relevant membership functions. The solution is obtained where the minimum membership value has been maximized, or the lowest level of satisfaction has been raised as high as possible. This decision criterion mimics the situation of multiple interest groups involved in the land allocation decision on Vancouver Island. The strength or viability of a consensus decision will be largely influenced by the level of commitment (degree of satisfaction) of the least committed group.

Model construction places implicit values on outputs; it is impossible to make a decision or rank alternative scenarios unless such values are assigned. By employing the fuzzy approach, as represented by maxmin, it is possible to avoid translating the objectives into common, perhaps unnatural or inappropriate, units of measurement as doing so can derail a multigroup negotiation problem. Through iteration and continued revision of the membership func-

![Figure 1. Illustration of a fuzzy decision space, defined by the intersection of a fuzzy goal and constraint.](https://academic.oup.com/forestscience/article/43/4/509/4627419/512)
tions, one would expect to arrive at some set of implied values, although not necessarily measured in dollar terms. Since iteration has not been possible in the case of the Vancouver Island decision, this study can merely suggest a framework for arriving at group consensus or decision. Therefore, despite its limitations and in the absence of good evidence to argue for another operator, the maxmin approach is used here; it is also favored in the literature (e.g., Hof et al. 1986, Hof 1993).

The decision model can now be written as a crisp LP. Suppose that the original fuzzy MODM is as follows:

\[
\begin{align*}
\text{find} & \quad x \\
\text{s.t.} & \quad A_i x \geq b_i \quad i = 1, 2, \ldots, N \\
& \quad x \geq 0, \quad (15)
\end{align*}
\]

where \( N \) is the number of goals plus constraints, \( A_i \) refers to the crisp parameter values, and \( \geq \) refers to fuzzy objective or constraint sets. Assuming linear membership functions, Zimmerman (1991) has shown that \( (15) \) can be written as:

\[
\begin{align*}
\text{max} & \quad \lambda \\
\text{s.t.} & \quad A_i x - b_i - d_i(\lambda - 1) \geq 0 \quad i = 1, 2, \ldots, N \\
& \quad x \geq 0, \quad (16)
\end{align*}
\]

where \( \lambda = \mu_{\beta_i}(x) \) and \( d_i \) is the spread of the \( i \)th fuzzy goal or constraint—the goal \( G_i(x) \) is completely unsatisfied for \( x \geq b_i - d_i \), completely satisfied for \( x \leq b_i \), and is partially satisfied over the intervening interval. This is the maxmin formulation of the fuzzy MODM. Other formulations exist, some of which employ a composite objective function, which is usually additive (see Mendoza and Sprouse 1989).

**Fuzzy Programming with Imprecise Coefficients**

Now consider the situation where the elements of the matrix \( A \) are not precisely known. The \( j \)th element of \( \tilde{A}_{ij} \), is described by a fuzzy number. Furthermore, assume that these fuzzy numbers are triangular and symmetric, allowing \( \tilde{a}_{ij} \) to be written as \( (m_{ij}, \beta_{ij}) \). A point on the numberline, \( n \), has a degree of membership in \( \tilde{a}_{ij} \) of:

\[
\begin{align*}
\mu_{\tilde{a}_{ij}}(n) &= 0 \quad \text{if} \quad n \leq m_{ij} - \beta_{ij} \\
\mu_{\tilde{a}_{ij}}(n) &= 1 + (n - m_{ij})/\beta_{ij} \quad m_{ij} - \beta_{ij} \leq n < m_{ij} \\
\mu_{\tilde{a}_{ij}}(n) &= 1 \quad \text{if} \quad n = m_{ij} \\
\mu_{\tilde{a}_{ij}}(n) &= 1 - (m_{ij} - n)/\beta_{ij} \quad m_{ij} < n < m_{ij} + \beta_{ij} \\
\mu_{\tilde{a}_{ij}}(n) &= 0 \quad \text{if} \quad n \geq m_{ij} + \beta_{ij} \quad (17)
\end{align*}
\]

This fuzzy number is depicted in Figure 2.

To capture the effect of uncertainty in the model parameters, we employ an \( \alpha \)-cut. This allows the definition of a crisp parameter value derived from the characteristics of the underlying fuzzy set, and permits the use of a standard LP format. From Figure 2, an \( \alpha \)-cut gives two possible realizations of \( \tilde{a}_{ij} \) (and \( \tilde{a}_2 \), which represent, respectively, the lower and upper bounds of the parameter. Consider the lower bound first. The imprecise nature of the technical coefficients is incorporated into model (16) to give the following structure (Lai and Hwang 1994):

\[
\begin{align*}
\text{Max} & \quad \lambda \\
\text{s.t.} & \quad [\tilde{A}_i - (1 - \alpha)\beta_i] x - b_i - d_i(\lambda - 1) \geq 0, \quad i = 1, 2, \ldots, N \\
& \quad \lambda \in [0, 1], \alpha \in [0, 1] \quad \text{and} \\
& \quad x \geq 0. \quad (18)
\end{align*}
\]

Model (18) permits each element in the parameter matrix to be adjusted to reflect the membership level being considered. Each element \( \tilde{a}_{ij} \) is transformed to give a crisp realization \( a_{ij} \) such that \( \mu_{\tilde{a}_{ij}}(a_{ij}) = \alpha \) the degree of membership of \( a_{ij} \) is \( \alpha \). When \( \alpha = 1 \), this MODM formulation is identical to the fuzzy MODM discussed previously. As \( \alpha \) decreases, parameter values move away from the center value, \( m_{ij} \), to values lying below \( m_{ij} \) on the defined interval. The solution is now derived using parameter values with a lower degree of membership. This case reflects the situation where the parameters considered most likely are greater than the true parameter values. The model in (18) sets all imprecise parameters to the same degree of membership, one distinct point in the range of possible solutions. The justification for doing so was discussed above.

If we replace \( \tilde{A}_i - (1 - \alpha)\beta_i \) in (18) by \( \tilde{A}_i + (1 - \alpha)\beta_i \), then the model uses higher values for the parameters that have the same degree of membership. This represents the situation where the most likely values lie below the true values.

Jointly, these two models provide an upper and lower bound for possible solutions by considering the two extreme points of the fuzzy numbers defined by \( \mu(\tilde{a}_{ij}) = \alpha \). As the decision maker is less confident that the central value of the fuzzy number is a correct representation of the true value, the \( \alpha \)-cut is lowered (this can be visualized by lowering the horizontal line in Figure 2) and the length of the interval separating these bounds increases. This interval identifies the range of possible solutions. Model (18) is restrictive in that it
A Decision Model for Land Use on Vancouver Island

Vancouver Island consists of nearly 3.35 million ha, of which 2.4 million ha is publicly owned and has been classified according to timber production potential. During deliberations, the Vancouver Island CORE employed the land use categories “high-intensity resource use,” “integrated resource use,” “low-intensity resource use,” “protected areas,” and “settlement” (van Kooten 1995). As public lands are the focus of this analysis, “settlement” lands and other private lands are ignored.

Goals reflecting the general public’s expectations regarding forest land use in B.C. are taken from the 1989 Parksville Old-Growth Workshop (B.C. Ministry of Forests 1990). They are as follows: (1) achieve a high revenue from timber harvest; (2) create additional benefits from forest recreation activities; (3) obtain the greatest possible nonuse benefits from forests, as measured in monetary terms; (4) maintain forest employment; (5) collect substantial direct revenues from the forest industry; (6) achieve a high contribution of the forest sector to provincial Gross Domestic Product (GDP); and (7) expand wilderness protection. Vague terminology renders each of these objectives fuzzy, and therefore the values for each cannot be known precisely. As discussed earlier, fuzziness is a measure of how well an instance or value conforms to a semantic ideal or concept. Hence, vagueness can be modeled through the specification of (one-sided) fuzzy objectives, while imprecision about parameter values can be modeled using fuzzy numbers.

Three types of MODM models for land-use decisions on Vancouver Island are compared to evaluate the usefulness of fuzzy MODM. The first is a crisp NPV maximizing formulation of the multiple goal problem. The second is a fuzzy multiple objective decision model that incorporates the fuzziness of objective values. Finally, a fuzzy multiple objective decision model with both fuzzy objectives and imprecise parameters is considered. The models are static and assume a planning period of 100 yr—the assumed rotation age of the working forest. The first step in the modeling process is specification of the parameters. These results will be summarized in Table 1. The figures described in the following sections refer to average situations, while those in Table 1 are for specific land types. This is the reason for any differences.

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<td>(21.9, 10)</td>
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<td>(0.0138, 0.0045)</td>
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<td>(0.0100, 0.0027)</td>
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<td>(603, 215)</td>
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<tr>
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<td>(21.9, 10)</td>
<td>(0, 0)</td>
<td>(0.0058, 0.0029)</td>
<td>(71, 49)</td>
<td>(349, 167)</td>
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<tr>
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<tr>
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<td>(6.7, 6.7)</td>
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<tr>
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<td>(6.7, 6.7)</td>
<td>(0.0087, 0.0026)</td>
<td>(107, 63)</td>
<td>(525, 199)</td>
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<tr>
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<td>(6.7, 6.7)</td>
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<td>(43.9, 10)</td>
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</tr>
<tr>
<td>Poor</td>
<td>(4, 53)</td>
<td>(43.9, 10)</td>
<td>(13.4, 13.4)</td>
<td>(0.0033, 0.0015)</td>
<td>(41, 30)</td>
<td>(202, 104)</td>
</tr>
<tr>
<td>Protected</td>
<td>—</td>
<td>(26.3, 10)</td>
<td>(26.8, 26.8)</td>
<td>—</td>
<td>—</td>
<td>—</td>
</tr>
</tbody>
</table>

* The first term defines the central value, the second the spread.

4 An additional objective mentioned was maximizing long-run sustained yield. However, since this does not seem a worthy objective in itself (rather it supports the six objectives listed in the text), it is not included in the analysis.

5 This approach is standard practice in forest economics to cope with multiple objectives. Maximization of social welfare or NPV is achieved by summing the various accounts (e.g., Tecle et al. 1994; Mendoza et al 1993).
Description of Imprecise Parameters

Logging Benefits

Logging benefits per hectare are calculated as the difference between the price and the cost of a cubic meter (m³) of delivered wood. Harvest volume is assumed to be a function of two harvest site attributes: site quality and management intensity.

Site quality is characterized as good, medium, or poor. Average harvest volumes by stand age, species, and site class, for the B.C. coastal region, are taken from the FOREST6.0 model (Phelps et al. 1990a, 1990b). Uncertainty as to the realized harvest from a particular site is captured by specifying a range of possible harvest volumes based on consideration of extremes provided by species composition and of a 20 yr spread in harvest age.

In this paper, an area is assigned to the “high intensity management” category if intensive silviculture (spacing, pruning, and precommercial thinning) is to be practiced. Under “integrated management,” it is assumed that basic silviculture (site preparation and replanting) will be performed. Land allocated to “low intensity” management provides harvest volume from naturally regenerated stock. No harvest is available from “protected” areas.

Harvest volumes available from each of these nine land allocation categories (three site qualities and three management categories) are described by a symmetrical triangular fuzzy numbers of the form \((m_p, M_p, B_p)\). The center value \(m_p\) is the arithmetic mean of the extreme values.

Ranges for wood prices, based on species, age, and management, are also taken from the FOREST6.0 simulation model, and fuzzy numbers for the price parameters are calculated as for wood volume. These distributions are scaled to reflect the average 1992 wood price of $70.71 m⁻³ for the Coast region (see Price Waterhouse 1993).

Calculation of delivered wood costs follows the methodology outlined above, with the exception that costs vary with management intensity but are constant across site qualities. Two cost values are reported for the B.C. coastal region, one for low cost and another for high cost sites. The fuzzy numbers are based on the mean of the two cost figures and are scaled to reflect an average cost of delivered wood after stumpage fees, rents, and royalties of $65.13 m⁻³ (Price Waterhouse 1993). These costs do not include costs of silviculture. The B.C. Ministry of Forests (1993) provides average cost data for silvicultural activity in 1992. Basic silviculture was applied at a cost of $21.20 ha⁻¹, while incremental silviculture represented an added expense of $20.00 ha⁻¹. These costs are added in the appropriate management categories. Net logging benefits are calculated as the difference of total revenue per hectare and total costs per hectare. Using the definitions of fuzzy addition, subtraction, and multiplication provided in Equations (8)–(11), we obtain symmetric fuzzy numbers. The results are summarized in Table 1.

Recreation Values

Recreation benefits are identified as a goal of land use planning. Recreation plus recreation option value for the Vancouver forest region are estimated at $111.11 million per year (B.C. Ministry of Forests 1991), for an average recreational value of $33 ha⁻¹ yr⁻¹. This value was obtained under the current management regime, which is denoted as integrated management in this study. Land under low intensity management is assumed to offer little in increased recreational opportunities compared to integrated management, with the same recreational activities being pursued and logging ongoing. Land under intensive management is assumed to produce only 50% of the benefits attainable under integrated management as intensive forestry practices compromise recreational opportunities. Protected areas, with potentially more stringent guidelines as to appropriate recreational activities, will provide only 40% of the benefits received from the integrated management regime. Centers for the fuzzy numbers are scaled to preserve the gross average of $33 ha⁻¹ yr⁻¹, with distribution spreads set at $10 ha⁻¹ yr⁻¹ for all classes.7 The results are summarized in Table 1.

Preservation Values

Estimation of preservation or nonuse benefits is based on a survey conducted by Vold et al. (1994) that determined the values that B.C. residents place on wilderness protection in the province. The mean maximum annual willingness to pay for a doubling and tripling of wilderness area from a base of 5% were $136 and $168 per household, respectively. We assume that the number of households on Vancouver Island is equal to the size of the labor force. Each household on the Island is then prepared to pay $32 yr⁻¹ ($168 minus $132) to increase the amount of protected area to 495,000 ha (15% of the total) from the current 10% level, corresponding to an average annual payment of $26.69 ha⁻¹ of protected area.8

Clearly the value of nonuse attributes falls with increasing management intensity, but there is little information for quantifying this relationship. The assumption is that low intensity management provides preservation benefits at 50% of that of protected areas, integrated management areas at 25% of the level of protected areas, and land under high intensity management is assumed to provide no nonuse benefits. Distribution spreads for these fuzzy numbers are set to allow the range of possible values to begin at 0 and extend to twice the hypothesized value. The results are summarized in Table 1.

Forest Sector Employment

Forest related employment may be generated both by the forest industry and by the forest-related tourism and recreation industry. Price Waterhouse (1993) reports 1.18 jobs per 1,000 m³ of wood harvested for the coastal industry. This estimate is reduced slightly to 1.16 jobs per 1,000 m³ to

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6 The negative value associated with harvest of poor sites is consistent with the current situation: most of the current harvest is obtained from the better quality sites, and there is no margin to allow harvest of the inferior site class.

7 The spread of $10 ha⁻¹ yr⁻¹ for recreation is based on our knowledge of studies that have sought to value recreation in the province of BC.

8 Preservation values are underestimated if part of the benefits accrue to people off Vancouver Island. On the other hand, they may be overestimated because the marginal value of nonuse attributes is assumed constant while the study by Vold et al. (1994) indicates that these values may well be declining.
reflect the fact that some of the jobs associated with the Island harvest are located in mainland mills. The spread for this fuzzy number is set at 0.07, consistent with the variation reported by Statistics Canada (see COFI 1992) for the past decade.

There is little information about the relationship between employment and other uses of the forest. Regionally based studies yield estimates of 0.0001 to 0.0003 jobs ha\(^{-1}\) (see Matas 1993, Clayton Resources Ltd., and Robinson Consulting & Associates Ltd. undated). The latter figure is used to anchor the job fuzzy number with relatively large spreads to reflect the high degree of uncertainty regarding their genesis.

**Direct and Indirect Government Revenue**

In 1992, the provincial government and municipalities received $5.27 m\(^{-3}\) of harvest, while the province collected $9.05 m\(^{-3}\) in stumpage fees for a total revenue of $14.32 m\(^{-3}\) (Price Waterhouse 1993). It is assumed that revenues can vary by as much as $5 m\(^{-3}\).

**Indirect revenues** are examined by looking at the contribution of forestry to provincial GDP. Forestry accounts for a substantial proportion of provincial GDP, indicating a high dependence on forest operations. Each cubic meter of harvest contributes about $70 to GDP. An interval of $20 m\(^{-3}\) is chosen. The results are summarized in Table 1.

**Expansion of Wilderness Protection**

There is nothing uncertain about the contribution of a hectare of land towards the objective of wilderness protection. It is a crisp parameter—1 ha of land allocated to protected area provides 1 ha of protected area.

**Objective Target Values**

The objectives are all modeled as fuzzy “greater than constraints.” Thus, the degree of satisfaction increases as the value of the objective function increases. The value deemed to be the lowest possible to generate any satisfaction of the objective defines the lower limit of the constraint interval \((b_l - d_l)\). The value deemed to be the lowest value at which complete satisfaction of the objective is attained defines the upper limit of the interval \((b_u)\). The degree of membership in the fuzzy objective set is given by a one-sided fuzzy number.

Two approaches can be used to determine the upper and lower values for the objectives. The levels may be provided by a decision-maker or an expert in the area, relying on a subjective understanding of both the limits inherent in the system as well as what would constitute a satisfactory level of achievement. In this paper, “employment” is incorporated using this approach. A second approach is to define the upper and lower bounds as the maximum and minimum levels that the system can provide when each objective is considered in isolation. This method may be especially suitable when objectives are less sensitive politically and not restricted to a narrow range *a priori*. Compared with the previous approach, this method is a more objective approach to defining the fuzzy constraints and is appropriate when there is little information available regarding the problem, preventing the initial specification of unrealistic objectives. In the current analysis, the objective “logging benefits” is incorporated using this approach.

For logging benefits, the level for complete satisfaction is set as the maximum available from the model if only logging benefits are considered. The minimum represents the amount generated from a working forest of 700,000 ha, even though such a scenario was rejected by CORE as too low. The lower and upper bounds for logging benefits are $48.1 million and $72.0 million, respectively. Recreation and preservation benefit intervals are defined by the maxima and minima available from the system. The lower and upper bounds for recreation are ($49.9 million, $90.1 million), and for preservation ($8.6 million, $60.0 million).

Employment is a politically sensitive issue. We assume that the current level provided by the forest industry is fully satisfactory, even though it will be difficult to maintain current employment in the future as technological developments lead to a decreasing number of jobs per unit of harvest. Jobs related to recreation are also considered satisfactory at current levels, although, in actual fact, it would probably be less than satisfactory if current levels were simply maintained. However, recreation contributes only a very small number of jobs compared to those related to timber harvest; requiring an increase in this component has little impact in the model. The lower bound for job provision is set arbitrarily at 15% below the current level (i.e., 13,500), on the assumption that it would be unwise politically for government to allow employment levels to drop below this figure. The upper bound is 15,700 jobs.

Maximal values for both direct and indirect revenue are determined by the ability of the system to generate revenues and timber-related GDP. Lower bounds again reflect the political nature of these objectives. It is assumed that a decrease of more than 20% in direct revenues, or of 25% in indirect revenues (i.e., forestry’s contribution to GDP), would be politically unsatisfactory. The bounds are ($139.2 million, $174.0 million) for direct revenue and ($640.5 million, $854 million) for indirect revenue.

The final objective is that of wilderness expansion. Any increase in protected areas will most likely come from Crown land. A doubling of protected area on the Island would mean that 660,000 ha would be removed from the working forest, or about 30% of total Crown land. It is assumed that protecting almost a third of the public land on Vancouver Island would allow all PAS objectives to be met; thus, the decision maker is assumed to be satisfied completely at that level of wilderness protection. The lower level for the fuzzy objective is defined as the current area under protection (341,000 ha), a level below current legislated requirements and so considered unacceptable.

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9 In this analysis, direct revenues to the provincial government do not include employee taxes paid as a result of indirect and induced employment, and revenues accruing to the federal government are ignored.

10 In theory, it would be preferable to use the second method to set initial parameters, and then use feedback information from users to refine the objective intervals, thereby incorporating new information on values or preference structure. The specification of satisfactory levels of achievement for this model employs a combination of the two approaches, without the benefit of any interactive procedure.
Table 2. Simulation results for fuzzy and crisp MODM: the resulting land allocation in hectares.

<table>
<thead>
<tr>
<th>Site quality</th>
<th>Management intensity</th>
<th>Crisp</th>
<th>Fuzzy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Good</td>
<td>High</td>
<td>223,845</td>
<td>209,848</td>
</tr>
<tr>
<td></td>
<td>Integrated</td>
<td>0</td>
<td>13,994</td>
</tr>
<tr>
<td></td>
<td>Low</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Medium</td>
<td>High</td>
<td>891,016</td>
<td>363,747</td>
</tr>
<tr>
<td></td>
<td>Integrated</td>
<td>0</td>
<td>527,269</td>
</tr>
<tr>
<td></td>
<td>Low</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Poor</td>
<td>High</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Integrated</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Low</td>
<td>754,644</td>
<td>658,671</td>
</tr>
<tr>
<td>Protected</td>
<td></td>
<td>341,000</td>
<td>436,976</td>
</tr>
</tbody>
</table>

Empirical Results

A crisp MODM (in the form of an NPV maximizing LP model), a fuzzy MODM and a fuzzy MODM with imprecise coefficients were constructed and solved. First, the results of the crisp formulations are compared to the fuzzy MODM with crisp parameters, which is then compared with the model where the coefficients are imprecise.

Fuzzy and Crisp MODM

The crisp MODM model (or CRISP) maximizes net present value (NPV) subject to employment and wilderness conservation constraints. NPV is defined as the sum of logging benefits, recreation benefits, nonuse values, and direct government revenues. The fuzzy MODM (FUZZY) considers all objectives of the previous section as independent and equal in terms of priority. The land allocations resulting from these models are presented in Table 2.

The CRISP model concentrates good and medium quality sites into high intensity management regimes, and allocates all poor sites to the low intensity system. In contrast, the FUZZY model places the larger proportion of medium quality forestland under integrated management as well as a small amount of good quality area. Total area assigned to the high management regime is less, and protected area is greater. Given that the B.C. government has indicated recently that logging should take better account of nontimber benefits, it is interesting to note that the outcomes of the fuzzy model are more in line with government policy than the outcomes of the crisp model. On the other hand, it must be noted that there is very little movement (if any) of high quality land into protected areas in both the crisp and the fuzzy models, which is at odds with the philosophy and intent of the PAS.

Differences in the allocation schemes are evident in the levels attained for each of the objective functions (see Table 3). The logging benefits are greater under the crisp formulation, and as a consequence so are direct government revenues and employment, but logging benefits are of such a magnitude that they dominate other forest services when weighed equally. The fuzzy model provides a higher return on the other accounts.

There is a membership function (\(\mu_i\)) associated with each of the objective functions indicating the level of satisfaction attained for each objective. Focusing on the FUZZY model, we find that the minimum degree of satisfaction is attained for four of the seven objectives (this table is not reported here). Given that the model provides an efficient solution, the interpretation is that it is impossible to increase the satisfaction level for any one of these four without compromising that of at least one of the other three. The standoff is between logging benefits and employment on the one hand, and preservation values and protected areas on the other. This situation reflects the reality of the conflicts identified in the Vancouver Island land use debate.

Perhaps the difference in performance between the crisp and fuzzy models can be explained by the fact that the former resembles a cost-benefit analysis whereas the latter is more like a true MODM. However, it is impossible to conclude to what extent the divergence between the crisp and the fuzzy models is caused by the difference between crisp and fuzzy modeling per se. Interpretation is blurred by the different nature of both models: maximizing NPV subject to constraints in the one and balancing objectives in the other.

A Fuzzy MODM with Imprecise Coefficients

Symmetric fuzzy numbers are used to model the uncertainty surrounding the precision of the parameters in the model. One purpose is to gain some understanding about the sensitivity of the solution to uncertainty in parameter definition. By lowering the value of \(\alpha\) (the fuzzy MODM has an implicit \(\alpha\) value of 1), the effect of this uncertainty on optimal land allocation can be explored. At any value of \(\alpha < 1\) there are two solutions to consider. The first is from the lower-bound version of model (18), where parameter values take on a less likely and lower value (the LOWER results); the second is from the upper-bound version of (18), generating a solution based on parameter values that have the same degree of membership in the

Table 3. Simulation results for fuzzy and crisp MODM: the resulting monetary and employment benefits.

<table>
<thead>
<tr>
<th>Benefits</th>
<th>Lower</th>
<th>Fuzzy</th>
<th>Upper</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(\alpha = 0.95)</td>
<td>(\alpha = 1)</td>
<td>(\alpha = 0.95)</td>
</tr>
<tr>
<td>Logging ($ mil.)</td>
<td>68.6</td>
<td>54.2</td>
<td>55.3</td>
</tr>
<tr>
<td>Recreation ($ mil.)</td>
<td>66.5</td>
<td>64.7</td>
<td>76.7</td>
</tr>
<tr>
<td>Preservation ($ mil.)</td>
<td>19.1</td>
<td>21.7</td>
<td>24.0</td>
</tr>
<tr>
<td>Direct revenue ($ mil.)</td>
<td>179.2</td>
<td>163.2</td>
<td>166.7</td>
</tr>
<tr>
<td>Indirect revenue ($ mil.)</td>
<td>875.9</td>
<td>806.3</td>
<td>814.8</td>
</tr>
<tr>
<td>Employment (jobs)</td>
<td>15,066</td>
<td>13,948</td>
<td>14,054</td>
</tr>
</tbody>
</table>

11 Although linear, the models were solved using a nonlinear algorithm within EXCEL.

12 Interestingly, both models provide an annual harvest that exceeds the current LRSY of 11.0 million m³. This is due largely to the application of intensive silvicultural practices to a substantial portion of the Crown land base, contrary to current conditions.
fuzzy number but higher value (the UPPER model results). The results from the two models are provided in Tables 3 and 4.

The most obvious result obtained from the variation of the degree of membership is in the asymmetry of the feasible solution space. While solutions may be obtained for any value of \( \alpha \) using the UPPER model, feasible solutions do not exist below a degree of membership level of 0.92 for the LOWER model. Parameter values are unable to provide any level of satisfaction of at least one of the objectives; in this case, the limiting objective is timber benefits.

An unexpected result is that the LOWER model, with \( \alpha = 0.95 \), provides for over 10% more protected area than do any of the other scenarios considered. The minimum amount is provided by the FUZZY model. The rationale for this is that the LOWER model concentrates the good and medium quality sites into the high intensity management category, a massive shift of almost 400,000 ha as compared to the integrated management allocation level of the FUZZY model. This occurs in response to the lower estimation of both wood yield and wood value. This causes a large reduction in nonuse benefits as the high intensity management category does not contribute to this objective. The shortfall is replaced by the allocation of poor quality area, with its negative logging value, into the protected area category.13 Harvest volume declines under this LOWER scenario, and job numbers fall slightly (Table 3). Monetary benefits are also slightly lower with the largest change observed in recreation benefits; logging benefits are virtually unchanged (Table 3).

It is our opinion that the dramatic effects of small parameter adjustments provides an additional reason to model the imprecision associated with parameter estimates explicitly.14 The evidence from Table 4 indicates that, if there is indeed imprecision in the parameters but it is not modeled as such [i.e., imprecise parameters are modeled as if they are crisp, possibly by tolerating small violations of constraints, as in Bare and Mendoza (1992), or Mendoza and Sprouse (1989)], then the results may be distorted. The analysis conducted here enables decision makers to identify sources of imprecision when it comes to land allocation. As information gathering is costly, and with limited funds available to overcome parameter imprecision, there is a definite value in knowing which areas to research first. Under the current conditions it seems that it is most crucial to address imprecision in the logging benefit parameters.

The results obtained from the UPPER model as \( \alpha \) is decreased are as expected. All parameters of the model increase in value as \( \alpha \) decreases, resulting in a higher provision of benefits from each hectare of land considered. Increasing yields and wood values allow less area to be allocated to the high intensity regime and more to integrated management. The result is an increase in both recreation and nonuse benefits. Harvest volume rises and job provision increases, evidence of the less possible higher per ha yield estimates and a greater number of jobs per unit of harvest.

### Conclusions

Increasing weight is placed on nontimber values in managing forests or making allocation plans for woodlands. The public is also becoming more involved in the planning process. Both trends are evident in British Columbia in the new forest management policies aimed at environmental concerns and a CORE process that relies on stakeholder participation. In most instances, economic efficiency is only one of many competing considerations, with cost-benefit analysis often relegated to a status below that of other concerns, such as employment. Hence, deci-

<table>
<thead>
<tr>
<th>Management intensity</th>
<th>Lower ( \alpha = 0.95 )</th>
<th>Fuzzy ( \alpha = 1 )</th>
<th>Upper ( \alpha = 0.95 )</th>
<th>Upper ( \alpha = 0.9 )</th>
<th>Upper ( \alpha = 0.80 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Good site quality</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High</td>
<td>223,842</td>
<td>209,848</td>
<td>136,697</td>
<td>69,680</td>
<td>0</td>
</tr>
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<td>Integrated</td>
<td>0</td>
<td>13,994</td>
<td>87,145</td>
<td>154,162</td>
<td>223,842</td>
</tr>
<tr>
<td>Low</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Medium site quality</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High</td>
<td>753,259</td>
<td>363,747</td>
<td>330,668</td>
<td>300,593</td>
<td>213,323</td>
</tr>
<tr>
<td>Integrated</td>
<td>137,757</td>
<td>527,269</td>
<td>560,328</td>
<td>590,423</td>
<td>677,693</td>
</tr>
<tr>
<td>Low</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Poor site quality</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High</td>
<td>543,453</td>
<td>658,671</td>
<td>645,434</td>
<td>632,048</td>
<td>605,625</td>
</tr>
<tr>
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<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Low</td>
<td>552,194</td>
<td>436,976</td>
<td>450,213</td>
<td>463,599</td>
<td>490,022</td>
</tr>
<tr>
<td>Protected area</td>
<td></td>
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<td>2,210,505</td>
<td>2,210,505</td>
<td>2,210,505</td>
<td>2,210,505</td>
<td>2,210,505</td>
</tr>
</tbody>
</table>

13 This is likely an unacceptable result if quality of protected areas is important.
14 In this specific analysis, the solution provided by the FUZZY model is sensitive to overestimation of the true parameter values. If values are realized at a generally lower level than those judged most likely, a large shift in resource allocation is required to obtain the best solution as judged by the maximization of minimum objective satisfaction.
cision models need to be sensitive to the existence of multiple objectives and the fact that the objectives themselves and the parameters that characterize them are imprecise and vague. This study applied fuzzy MODMs with and without incorporating imprecise coefficients, to the problem of allocating public forestland on Vancouver Island, comparing the results of the fuzzy models with a more traditional, crisp approach.

Given the nature of the process that is to be modeled, our conclusion is that the fuzzy approaches can be judged a distinct improvement over the traditional approach of constrained maximization of net present value. For example, the fuzzy MODM allocated about 25% of the land base to integrated timber management, while the traditional (crisp) model concentrated land into the extreme categories of low (natural regeneration) and intensive timber management intensity. Given the intensity of the land use conflicts on Vancouver Island and the context of consensus seeking interest groups, moderation of management intensity seems desirable. The area assigned to the protected category was greater in the fuzzy MODM than in the crisp model, as was the number of direct jobs provided in the forest sector. We conclude that the decision by CORE not to rely on maximization of NPV is confirmed by comparing the results of the crisp and fuzzy models. The fuzzy solution was obtained without needing to specify precise values for objectives, and without an explicit ranking or weighing of the objective functions (the analysis does require estimating central values and spreads). The fuzzy MODM also clearly identified those objectives that were in direct conflict with each other, and thus the areas where compromise is required if satisfaction levels are to be increased.

The results from the fuzzy MODM model with imprecise coefficients suggest that the approach of combining fuzzy parameter specifications with fuzzy objectives constitutes an improvement over the fuzzy MODM. However, the model specified in this study was very sensitive to the possibility of lower realizations of parameter values, but this only highlights the importance of modeling imprecise parameters using fuzzy numbers instead of flexible constraints. The analysis provides an insight in what kind of additional information is especially valuable for obtaining robust land allocations—robust in the sense that small misspecifications of parameters will not cause massive shifts from one land use option to another, which in practice may be costly to achieve.

Finally, areas for future research suggest themselves. The most important of these is that of getting stakeholders/decision makers involved in the development of both fuzzy objectives and fuzzy numbers for the technical coefficients of the decision model. Fuzzy set theory offers a means of combining information from various stakeholders. Research is required to determine how information can be updated when those involved in the decision process are presented with results and, just as importantly, how natural language can be used to develop the required fuzzy measures.

Literature Cited


