

Computer Applications in Sustainable Forest Management

*Including Perspectives on Collaboration
and Integration*

Edited by

Guofan Shao

Purdue University, West Lafayette, IN, U.S.A.

and

Keith M. Reynolds

USDA Forest Service, Corvallis, OR, U.S.A.

Chapter 8

COMPUTER-AIDED DECISION MAKING*

Keith M. Reynolds¹ and Daniel L. Schmoldt²

¹*U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station, 3200 SW Jefferson Way, Corvallis, Oregon 97331, USA;* ²*U.S. Department of Agriculture, Cooperative State Research, Education & Extension Service, Waterfront Centre, 800 9th Street SW, Washington, DC 20024, USA*

Abstract: Several major classes of software technologies have been used in decision making for forest management applications over the past few decades. These computer-based technologies include optimization, expert systems, network models, multi-criteria decision making, and integrated systems. Each technology possesses unique advantages and disadvantages, and has been applied differentially to decision making in forestry. Several example DSS highlight the incorporation of these various technologies for vastly different management problems. Likely future development trends for decision support technologies over the next few decades include: Internet implementations, agent-based applications, increased social science components, and participatory decision making. As with most other computer applications, in general, we expect that decision support will transition to ever smaller devices that will take advantage of ubiquitous computing.

Key words: Decision support; decision making; optimization; expert systems; networks; multi-criteria decision models; integrated systems.

1. INTRODUCTION

Almost 30 years ago, Mintzberg et al. (1976) proposed a general model for the decision-making process (Figure 8-1). The Mintzberg model has stood the test of time; it is still widely accepted today as a general description of the multiple alternative processes and pathways that individuals and organizations use to get from problem recognition to problem resolution, which culminates in some course of action. Any software system that

* The US Government's right to retain a non-exclusive, royalty-free licence in and to any copyright is acknowledged.

explicitly assists with the implementation of one or more components of the overall process can be described as a decision-support system (DSS). Holsapple (2003, p. 551) nicely captures the essential features of a DSS as:

A computer-based system composed of a language system, presentation system, knowledge system, and problem-processing system whose collective purpose is the support of decision-making activities.

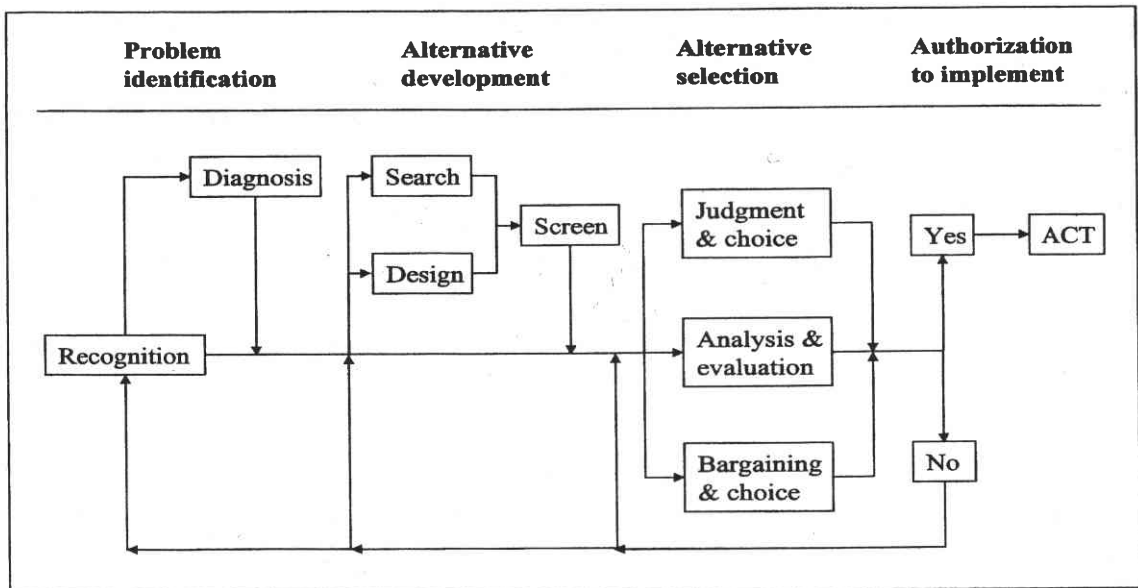


Figure 8-1. The Mintzberg planning process (Mintzberg et al., 1976), after Rauscher (1999). The Mintzberg process presents a general approach to planning, representing all, or at least most of, the classic variations on any planning process. Planning proceeds through the four steps of problem identification, alternative development, alternative selection, and a final decision to either implement the selected alternative, or cycle back to one of the first three steps. In each of the first three steps, multiple pathways are possible.

Two key attributes in the Holsapple definition are a subsystem for processing problems and purposeful support of a decision-making process. Many DSS focus exclusively, or nearly so, on the alternative-selection phase of the overall process (Figure 8-1). Some examples of systems that conform to the Mintzberg and Holsapple definitions and that usually focus on the alternative-selection phase include optimization systems, expert (or knowledge-based) systems that provide a framework for applying procedural or reasoning knowledge to decision problems, neural networks, Bayesian belief networks, and multi-criteria decision making, e.g., the analytic hierarchy process.

This chapter provides an introduction to DSS technologies as they have been applied to decision making in forest management. In terms of the underlying theories and technologies, the breadth and depth of this subject are enormous. Several to many volumes typically have been devoted to each of the topics covered in the following sections. So, we make no pretense to a comprehensive treatment of the subject. Instead, this chapter is intended to serve more as a roadmap for students of digital technologies with an interest in decision making, by suggesting approaches that may be worth investigating further.

In the following sections, we begin by looking at the origins of DSS, review several of the contemporary technologies including a few notable examples from forest management that demonstrate more comprehensive approaches to decision support, and speculate a little on the direction in which DSS development for forest management is likely to head in the near future.

2. MATHEMATICAL PROGRAMMING

Perhaps the earliest form of DSS to achieve widespread use in forest management was an approach based on optimization. The Forest Planning (FORPLAN¹⁰) system was developed by Johnson (1980, 1987), and was the primary analytical system used in strategic planning for national forests in the United States throughout the 1980s and into the early 1990s (Iverson and Alston 1986). The basic objective of any FORPLAN model is to optimize resource allocation and scheduling on a management area within a specified time frame, given well defined management objectives and constraints.

Use of mathematical programming as a basic tool for strategic forest planning has declined somewhat in the United States since the 1980s, in part because the black-box solutions of such systems pose a liability for resource management agencies (Gustafson et al. 2003). In particular, the difficulty of explaining the derivations of FORPLAN solutions was perhaps the most problematic issue (O'Toole 1983), given enormous public interest in the management implications of model solutions. Nevertheless, mathematical programming remains a popular and viable approach to decision support for strategic planning as evidenced by the continued use of the Spectrum system (http://www.fs.fed.us/institute/planning_center/plan_spectrum.html), a later evolution of FORPLAN, now maintained by the U.S. Department of

¹⁰ The use of trade or firm names in this publication is for reader information and does not imply endorsement by the U.S. Department of Agriculture of any product or service.

Agriculture, Forest Service. Key attributes of Spectrum (anonymous) include:

- Multi-resource modeling. The system provides a generic framework for modeling any resource. A basic configuration depends on user-defined analysis units, management actions, activities and outputs, resource coefficients, and economic information.
- Spatial and temporal scales. Spectrum applications are not scale-specific. Up to 90 time periods of any length may be used to support analysis at relevant spatial and temporal scales.
- Multiple options for mathematical programming. Spectrum supports numerous combinations of optimization techniques and objective functions. Optimization techniques include:
 - Linear programming (optimization of a single criterion).
 - Mixed-integer programming (optimization with categorical outcomes).
 - Multi-objective goal programming (simultaneous optimization of multiple goals).
 - Stochastic programming to account for random events such as fires, pest epidemics, and uncertainty about data.
- Specifications for objective functions. Options for objective functions in traditional linear programming include maximizing or minimizing a single outcome or measure of performance. Objective functions for goal programming include minimizing under-achievement of goals, minimizing over-achievement of goals beyond thresholds, or minimizing both. Two additional options for objective functions are MAX/MIN (maximizing the minimum level of occurrence for a critical resource) and MIN/MAX (minimizing the highest level of occurrence of an undesirable outcome).
- Simulation of ecological processes and modeling natural disturbance. Spectrum allows embedding simulation of ecological processes and modeling of natural disturbances by means of state, flow, and accessory variables in dynamic equations.

The Regional Ecosystems and Land Management (RELM) system extends the utility of Spectrum solutions by apportioning forest-wide, strategic planning solutions to tactical sub-units of the forest such as watersheds (http://www.fs.fed.us/institute/planning_center/plan_relm.html). Cumulative effects and connected actions can be analyzed both within and between sub-units, allowing planners to evaluate how alternative management scenarios affect neighboring units.

3. EXPERT SYSTEMS

Expert systems operate on knowledge to solve problems in a manner somewhat analogous to human reasoning, based on concepts and principles from artificial intelligence (Jackson 1990, Waterman 1986). Typical applications of expert systems include diagnosis, classification, and prediction. They have evolved as a class of DSS technology to deal with problems not otherwise readily amenable to conventional computational solutions such as optimization, simulation, and statistical methods. The essential components of all such systems are a set of facts and rules (collectively, a knowledge base), an inference engine that interprets and schedules execution of rules, and one or more interfaces for the development and execution of an application (Figure 8-2). One of the more attractive features of these kinds of systems is that nearly all provide some form of explanation facility that helps a system user understand the derivation of solutions.

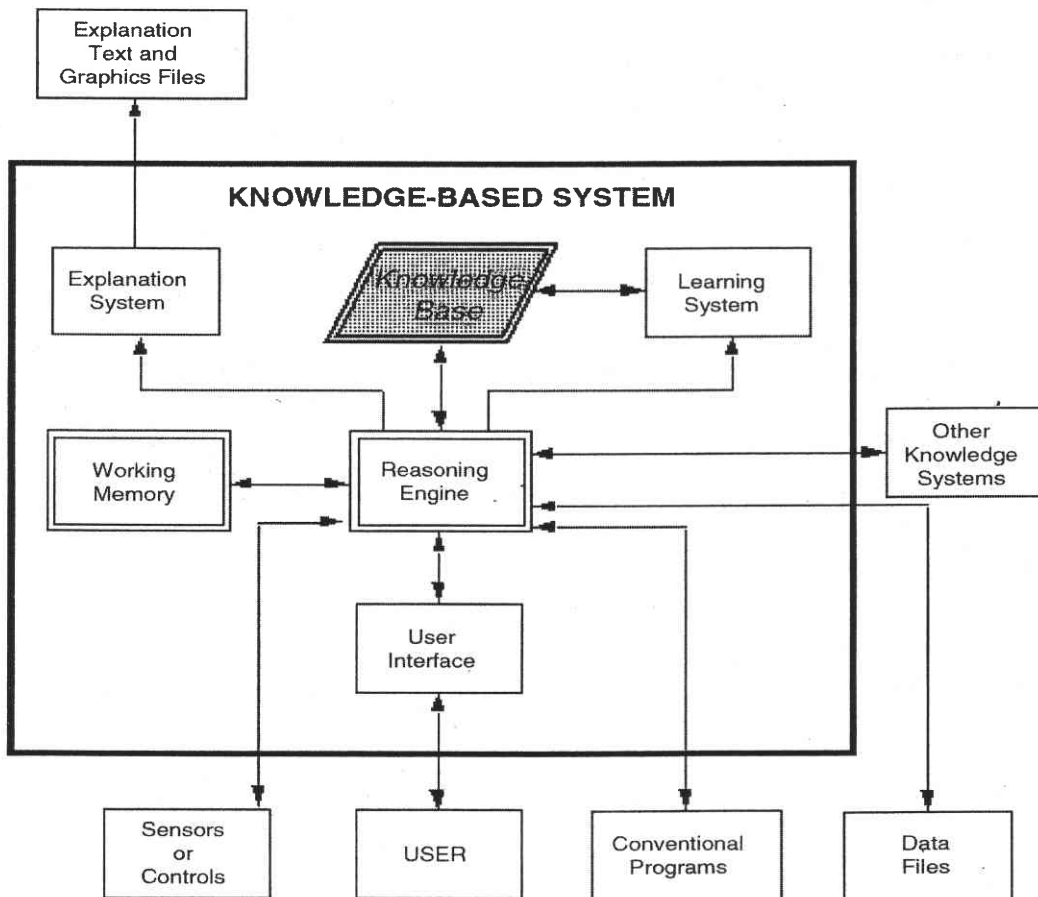


Figure 8-2. Basic components of an expert (or knowledge-based) system (Rauscher and Reynolds 2003).

MYCIN (Buchanan and Shortliffe 1984) is an early example, and still one of the most famous examples, of an expert system that was designed to provide medical diagnoses. The C Language Integrated Production System (CLIPS) was one of the earliest expert system development environments, and was developed at the Johnson Space Center of the National Aeronautics and Space Administration, beginning in 1984. CLIPS continued to evolve over the years (Giarratano and Riley 1998), is still widely used, and is available through the public domain (<http://www.ghg.net/clips/CLIPS.html>).

Expert system applications in forestry began appearing in the late 1980s (Schmoldt and Martin 1986). Some examples include a diagnostic and risk assessment tool (Schmoldt 1987, Schmoldt and Martin 1989) for insect and disease outbreaks in red pine (*Pinus resinosa*), an advisory system providing stand prescriptions for deer and grouse (Buech et al. 1989), a silvicultural system for managing red pine plantations (Rauscher et al. 1990), and a system for diagnosing the hazard and risk of bark beetle outbreaks in Alaska (Reynolds and Holsten 1997). Numerous other expert systems were developed to assist with forest pest management, silvicultural prescriptions, and timber harvesting, among other things (Durkin 1993). Developed initially as stand-alone software, eventually expert systems were integrated with optimization, simulation, geographic information systems (GIS), and other technologies covered elsewhere in this text.

4. NETWORK-BASED MODELS

Network theory has produced several successful approaches to representing problem-solving knowledge as a means of delivering decision support. Three of the more successful, and which are in relatively common use today, include artificial neural networks (ANN), Bayesian belief networks, and logic networks, each of which is described in the following sections. All three of these network-based systems have their roots in artificial intelligence, and, like expert systems, are well suited to applications such as diagnosis, classification, and prediction although each has particular strengths as discussed subsequently. Expert systems are often referred to more generically as *knowledge-based systems*, and this term applies equally well to Bayesian belief networks, and logic networks, so we will use this term hereafter as more preferable on both practical and epistemological grounds (it is not always easy to define what constitutes expertise, and it may even be regarded as a matter of opinion).

4.1 Artificial neural networks

System designs for ANN (Figure 8-3) were inspired by neuroscience and its understanding of the biological neuron (Wasserman 1989). Although common uses of ANN include diagnosis, classification, and prediction as already mentioned, perhaps their greatest potential is the general area of pattern recognition, e.g., Schmoldt et al. (1997) (that is, a form of classification, Turban and Aronson 1998, Zhang 2000). Notable examples of ANN development systems include Brainmaker (<http://www.calsci.com>) and Alyuda (<http://www.alysuda.com>), but many other systems exist (see, for example, http://www.it.uom.gr/pdp/DigitalLib/Neural/Neu_soft.htm).

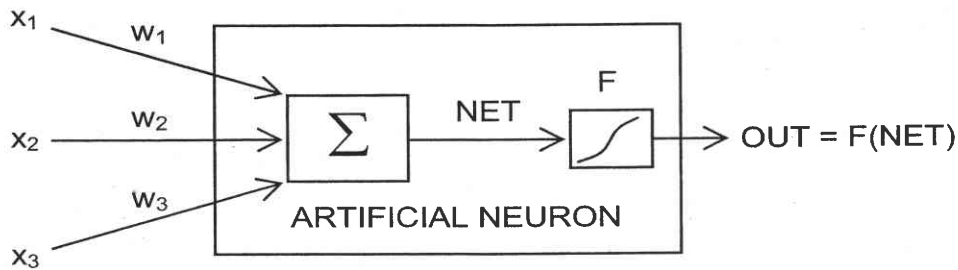


Figure 8-3. The basic architecture of an artificial neuron, after Wasserman (1989). Artificial neural networks are typically composed of two or more layers of such neurons.

One of the more interesting aspects of these types of systems is their demonstrated potential for learning, generalization, and abstraction (Wasserman 1989), in some respects fulfilling some of the early expectations for expert systems (q.v., Feigenbaum 1977, Winston 1977, Duda and Gaschnig 1981) that never really materialized. On the other hand, as Wasserman also notes, ANN are not a panacea. They can make mistakes, training procedures can produce suboptimal results or may fail to converge to a solution at all, and determining an optimal network design can be difficult. Moreover, like optimization systems, ANN have the same *black box* liability: they may produce reliable, accurate results, but there is no good intuitive explanation for their results that can be readily derived from the network structure itself.

ANN have been applied in a variety of contexts for forest management, including prediction of forest cover type (Blackard and Dean 1999), classification of ecological habitats (Liu et al. 2003), and detection of forest fires (Arrue et al. 2000). Notice that each of these applications is an example of pattern recognition in the broad sense. For these very technical and highly specific applications, lack of explanation facilities might not be viewed as a

significant liability. Peng and Wen (1999) and Schmoldt (2001) review several additional applications in forest management.

4.2 Bayesian belief networks

Bayesian belief networks (or simply Bayesian networks hereafter) make use of Bayes' theorem from probability theory to model the likelihood of events by explicitly representing conditional dependencies between variables of a problem domain (Pearl 1988). Not surprisingly, Bayesian networks find their most natural application in prediction, because the inference process derives from the likelihood of events. A Bayesian network encodes assertions of conditional independence in a directed acyclic graph that provides an intuitive graphical representation of the relevant knowledge, including interactions among the various sources of uncertainty (Howard and Matheson 1981). Netica (<http://www.norsys.com/index.html>) is perhaps the most well known development system for design of Bayesian networks, but a number of such systems are available (see, for example, http://powerlips.ece.utexas.edu/~joonoo/Bayes_Net/bayes.html#belief).

A significant claim for Bayesian networks is that they provide a parsimonious representation of conditionality among variables that makes it practical to model real-world problems more effectively than methods for determining causal relationships based on more traditional probability theory (Pearl 1988). For example, independence among variables is easy to recognize in the graph representation employed by most development systems, and conditional dependencies can be easily recognized in the directed graph. As a result, a model based on a Bayesian network need not consider all possible joint probabilities, and extraneous pathways can be ignored. A uniquely powerful feature of Bayesian networks is that even though causation in these graphs is unidirectional, Bayes' theorem allows us to reason backwards from events to evidence.

Ellison (1996) described an interesting application of Bayesian networks to directly support the adaptive management process (Holling 1978, Walters 1986):

Adaptive management is precisely analogous to an iterative Bayesian learning and decision process. Prior information is specified, decisions are made, and consequences are observed. The consequences are treated not as final events, but as new sources of information (new prior probability functions) for subsequent "experiments" (events, likelihood functions) that lead to modifications in management practices (new decisions).

Although Bayesian inference has been used very successfully in ecological research, it has not been widely adopted to date by resource managers as an approach to decision making (Ellison 2004). Lack of application in this context has been attributed, among other things, to “requirements for precise quantification of management options and their associated utilities or outcomes” (Ellison 2004). Perhaps, decision analysts and researchers need to work more closely with managers to develop useful applications of Bayesian networks.

4.3 Fuzzy logic networks

In the early years of knowledge-based system development, prevailing conventional wisdom held that such systems were best suited for very narrow, well defined problems (Waterman 1986). This is clearly reflected in the catalog of systems documented by Durkin (1993). However, the integration of fuzzy logic (Zadeh 1975a, 1975b, 1976) into knowledge-based systems in the early 1990s, as exemplified in systems such as a fuzzy version of CLIPS (Giarratano and Riley 1998) and NetWeaver (Miller and Saunders 2002) opened up new possibilities for applying knowledge-based methods. This marriage of technologies permitted application to much more general and abstract kinds of problems related to the management of natural resources, in general, and forest management in particular (Reynolds 2001a, 2001b).

Models based on fuzzy membership, such as those designed with NetWeaver, are commonly used to express strength of evidence for propositions that the model is entertaining (Figure 8-4). In this context, fuzzy logic is being applied in the sense of interpretation, and the model can be construed as a form of formal argumentation (Halpern 1989). Similar to Bayesian networks, however, a fuzzy membership function also can be used to express subjective probabilities (Zadeh 1968), in which case it may not be immediately obvious which form of knowledge representation is most preferable. As a basic guide:

- Bayesian networks are clearly preferable to fuzzy models if the problem at hand can be strictly represented in terms of the likelihood of events, and actual data are available to estimate the likelihood of those events.
- Bayesian networks may still be preferable to fuzzy models if the problem at hand can be strictly represented in terms of subjective probabilities (replacing the likelihood of events). The case for the Bayesian preference is not nearly as compelling in this situation, but the concepts of linguistic uncertainty underlying fuzzy logic are much less familiar to potential users and their clients, and this could be perceived as a liability, albeit not a major one.

- For more general problems involving both prediction and interpretation, or strictly interpretation or classification, fuzzy models become the better choice.

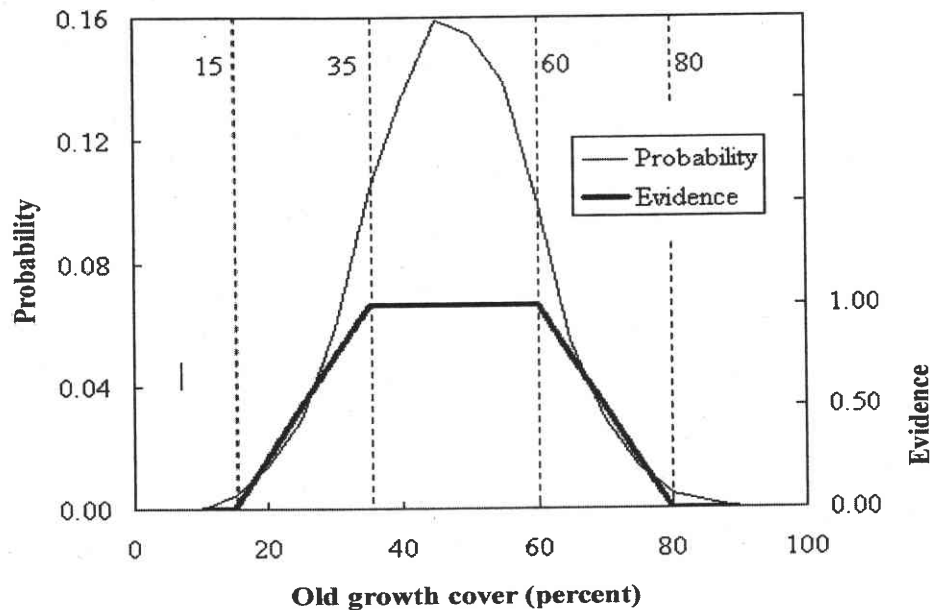


Figure 8-4. Specification of a formal argument with fuzzy logic.

5. MULTICRITERIA METHODS

The early successes of operations research (optimization) methods, described above, resulted primarily from their focus on well-constrained problems in tactical planning. These methods were initially developed to address needs in industrial and business operations, where inputs, outputs, resources, actors, flows, and other problem components could be described with completeness and certainty. Gradually these operations research methods were applied to planning in forest and natural resources management – primarily timber harvesting, transportation, and processing with their similarities to industrial operations.

Traditional optimization-based decision analysis has excelled in addressing mathematically well-defined problems and in addressing the quantitative components of larger problems. Nevertheless, numerous sources (e.g., Klein and Methlie 1990, Gigerenzer and Todd 1999; Levy et al. 2000, Romero and Rehman 2003) have noted that such formulations, while

mathematically and logically sound, simply do not reflect real-life problems faithfully enough. In reality, the decision maker is frequently looking for a *compromise* among several objectives. To address this new class of decision problems, multiple criteria decision making (MCDM) techniques were developed beginning in the 1970's. Stewart (1992) provides a review of those approaches. While optimization methods aim to maximize a single criterion over a non-enumerable solution space, MCDM maximizes the aggregate contribution of several criteria (or attributes) over a relatively small set of solution alternatives.

5.1 Multi-attribute utility theory

One of the earliest MCDM methods is multi-attribute utility theory (MAUT) or value theory (Keeney and Raiffa 1976, von Winterfeldt and Edwards 1986). In its simplest form, MAUT provides a set of utility functions (one function for each attribute, or performance indicator), and then scores each decision alternative on each attribute. Scores across all attributes are combined for each alternative (often using an additive model), with individual attribute scores being appropriately scaled for comparability and weighted according to importance. The decision alternative with the highest aggregate utility (or value) score is then preferred. This general MAUT framework has spawned a large number of variants. Each variant modifies one or more aspects of the traditional implementation: to assign weighting values, to scale attribute scores, to combine scores across attributes (e.g., non-additive models), to elicit utility functions, etc. As a result, MAUT has been modified in a wide variety of ways. Furthermore, MAUT has been augmented by other multiple criteria decision methods and other decision aides to make it more complete in some cases, and to improve its applicability in other cases.

5.2 Analytic hierarchy process

Another MCDM approach that was developed about the same time as MAUT and has all its basic characteristics is the analytic hierarchy process (AHP). The AHP, developed by Saaty (1977), provides for: decomposition of the decision problem into a multi-level hierarchy of criteria, direct pairwise comparisons of the decision alternatives (or alternatively, rating them individually), and rigorous mathematics to generate a preference structure for the alternatives. Schmoldt et al. (2001) describe many applications of the AHP to environmental and natural resources decision making. While many have used the AHP as an MCDM technique by itself, others have used it in combination with other MCDM methods (e.g., Prato 1999, Lexer 2000, Hill

et al. 2005). In other MCDM developments, Leskinen et al. (2003) have used statistical methods to estimate ecological values and to account for interactions among the decision variables. Drechsler (2004) demonstrated the integration of quantitative population models with MCDM to evaluate decision conflicts. Recently the network structure of the analytical network process has been used to model the complexity of forest decision problems in evaluating sustainable forest management strategies by using a criterion and indicator approach (Wolfslehner et al. 2005). These several examples, and many others not cited, attest to the versatility and extensibility of MCDM methods in general.

6. INTEGRATED SYSTEMS FOR FOREST MANAGEMENT

By the late 1980s, the scope of forest management began to expand dramatically as agencies, universities, and industry began to embrace new concepts such as the hierarchical organization of ecosystems (Allen and Starr 1982) and forest ecosystem management (Holling 1978, Walters 1986). With an emphasis on broad, holistic, integrated perspectives, the concept of forest ecosystem management posed serious new challenges to the delivery of effective decision support (Schmoldt and Rauscher 1996, Rauscher 1999). The challenge was further exacerbated by the still newer concept of sustainable forest management (SFM) that had risen to prominence, following the Earth Summit in Rio de Janeiro, Brazil in 1992, and by introduction of the adaptive management concept (Walters, 1986, Walters and Holling 1990). While adaptive management as a strategic guide has been useful, much about sustainable forest management remains a moving target. Consequently, holistic and integrative software tools have evolved largely through a trial and error development process.

Most of the DSS technologies discussed up to this point can be described as single-purpose systems designed for problems with a relatively specific focus. In contrast, spurred by the new challenges of ecosystem management, adaptive management, sustainable forestry, and similar concerns, a new class of systems began to emerge in the 1990s. Rauscher (1999) characterizes these new technologies as more "full-service" systems, in the sense that they integrate a few to several features and functions that collectively are designed to accommodate larger, more complex and abstract issues requiring decision support.

Reynolds (2005) provides a critique of three full-service systems that have achieved substantial recognition and are in relatively wide used: the Landscape Management System or LMS (<http://lms.cfr.washington.edu>),

NED (Twery et al. 2003, <http://www.fs.fed.us/ne/burlington/ned>), and the Ecosystem Management Decision Support (EMDS) system (Chapter 18, Reynolds et al. 2003a). A brief overview of each, from Reynolds (2005), is presented in the following subsections. A fourth system, Woodstock (<http://www.remsoft.com>), comparable to the others and notable for its success as a commercial application, is also discussed.

6.1 LMS

A wide variety of software applications are available to support decision making in forest management, including databases, growth and yield models, wildlife models, silvicultural expert systems, financial models, geographical information systems (GIS), and visualization tools (Schuster et al. 1993). Typically, each application has its own interface and data format, so managers must learn each interface and manually convert data from one format to another to use combinations of tools. Considering the scope of topics that may need to be addressed in a typical ecosystem management problem, and consequently the need to run several to many applications, manual orchestration of the entire analysis process can quickly become a significant impediment. LMS relieves this problem by managing the flow of information through predefined pathways that are programmed into its core component.

LMS integrates landscape-level spatial information, stand-level inventory data, and distance-independent individual tree-growth models to project changes on forested landscapes over time. The core component of the application coordinates the execution of, and flow of information between, more than 20 programs, including a variety of utilities for data management such as formatting, classification, summarization, and exporting.

Stand projections in LMS are performed with variants of the Forest Vegetation Simulator or FVS (Crookston 1997) or ORGANON (Hester et al. 1987). A variety of utilities report stand projection information in tables and graphs, and projection information can be delivered to the ArcView GIS (Environmental Systems Research Institute) for additional spatial analysis, or to the Stand Visualization System (SVS) or to the Envision landscape visualization system (McGaughey 1997). Both forms of output data can be valuable. In some cases, it is useful to analyze projection data further using a spreadsheet or statistical software, while other times it is most instructive to simulate the appearance of a stand to qualitatively assess spatial landscape features (e.g., scenic vistas).

6.2 NED

NED version 2.0 assists natural resource managers with project-level planning and decision-making processes, and is designed to be used by a forest management professional as a communication tool for working with forest landowners. NED is a goal-driven DSS that implements the Mintzberg et al. (1976) multiple-criteria decision-analysis process. Resources currently addressed include visual quality, ecology, forest health, timber, water, and wildlife. The system is adaptable to a range of applications from small private holdings to cooperative management across multiple ownerships. NED supports a five-step process:

1. Identify and define goals and their measurement criteria.
2. Inventory the property being managed.
3. Design alternatives to manage the land and satisfy the goals.
4. Simulate the impact of each alternative to visualize how the forest will look under each alternative.
5. Evaluate how well each alternative satisfies the hierarchy of goals, and possibly cycling back to step 3 to refine alternatives (e.g., an iterative process).

Extensive hypertext support provides information about resource goals, desired conditions that support the goals, data used to analyze forest condition, and detailed information about the program itself and the rules and formulae used to produce analyses.

NED uses a blackboard architecture and semi-autonomous agents to manage a variety of applications for the user (Nute et al. 2003). In the blackboard approach to problem solving, the current state of the solution is maintained in a global data store (i.e., the blackboard). Agents with specialized knowledge contribute their knowledge, incrementally building up a solution. Finally, a controller agent implements one or more solution strategies to orchestrate when and how other agents contribute to the solution (Nii 1989). The specialized agents participating in a blackboard solution are said to be semi-autonomous, as opposed to autonomous (Maes 1991), because they carry out their tasks under the supervision of a controller. In their simplest form, semi-autonomous agents have state (they "know" certain facts), and behavior (they perform certain tasks when certain states are recognized). Each specialized agent in NED, for example, has the procedural knowledge – or methods in the sense of object-oriented design (Booch 1995) – needed to operate a class of decision support tools needed in forest management. The simulation agent sets up input for growth and yield models and interprets model output. The GIS agent merges information with an ArcView shape file and invokes ArcView to display the information. The visualization agent generates input for SVS and Envision (McGaughey

1997). The NED blackboard is implemented as a data base with integrated Prolog clauses, and is managed by a controller agent. The interface agent provides access to all applications in the system through a single user interface. Additional agents support development of alternative treatment plans; provide analysis of timber, wildlife, water, ecology, and visual goals; and generate a wide variety of reports relevant to forest management. The net effect of tool integration in LMS and NED is similar: transparent flow of information among collaborating system components, resulting in improved ease of use for end users. However, from a development perspective, the agent architecture of NED more readily supports continuing system evolution by better facilitating integration of new decision support tools as they become available.

6.3 EMDS

The Ecosystem Management Decision Support (EMDS) system (version 3.1) is an extension to ArcMap, a component of the ArcGIS 9.0 (Environmental Systems Research Institute, Redlands, CA), that provides integrated decision support for environmental evaluation and planning at multiple spatial scales (Reynolds et al. 2003a). System architecture is based on the Microsoft Component Object Model (COM) specification, which supports the evolutionary design and implementation of complex systems by establishing communication standards that facilitate collaboration among system components (Potter et al. 2000). The practical significance of conformance to the COM specification is the ease with which the functionality of applications can be extended by integration of new components, as is well illustrated by the extensibility of ArcGIS itself via COM-based extensions.

The evaluation component of EMDS, implemented by Rules of Thumb (North East, PA), uses the NetWeaver logic engine (also Rules of Thumb) to evaluate knowledge bases, represented by networks of topics, concerning the state of landscape features. In design of a NetWeaver model, a topic for evaluation is represented by a testable proposition. The statement of a particular proposition may be quite vague. For example, in the SFM context, the statement, "The forest ecosystem is sustainable," clearly is relevant, but also quite vague. However, the formal logic specification underlying a proposition makes the semantic content of the proposition clearer and more precise (see Reynolds et al. 2003b for an extended example). The proposition about forest ecosystem sustainability evaluates as *true to the degree that* its premises are satisfied. The phrase, "true to the degree that," reflects an approach to problem specification that might be termed "evidence-based reasoning," and is implemented in NetWeaver models with

fuzzy math (Miller and Saunders 2002), a branch of applied mathematics that implements qualitative reasoning as a method for modeling lexical, as opposed to stochastic, uncertainty (Zadeh 1975a, 1975b, 1976). The reader is referred to the Fuzzy Networks section above.

The planning component, implemented by InfoHarvest (Seattle, WA), evaluates AHP decision models, components of which may optionally implement the Simple Multi-Attribute Rating Technique or SMART (Kamenetzky 1982). The SMART method evaluates attributes of alternatives with utility functions and, in the context of landscape planning, facilitates evaluating an arbitrary number of alternatives.

Logic models and decision models used in EMDS are built by application developers with the NetWeaver Developer (Rules of Thumb) and Criterium DecisionPlus (CDP, InfoHarvest) applications, respectively. The complete suite of applications (EMDS, NetWeaver Developer, and CDP) collectively provides a general application framework. An individual EMDS project may include evaluation and planning at multiple spatial scales, and networks of dependencies between scales can be designed by application developers by summarizing model outputs from one scale and passing them as inputs to models at coarser or finer scales. For example, knowledge base outputs from a biophysical evaluation of watersheds and a socioeconomic evaluation of counties may be summarized for input to the evaluation of biophysical provinces or ecoregions.

6.4 Woodstock

The Remsoft Spatial Planning System (RSPS) is a commercial software suite for long-term forest management planning (Remsoft 2005). The system integrates four separate components that work together to help forest managers formulate strategic management plans that are feasible both tactically and operationally. In contrast to the first three general DSS discussed in this section, all of which at least tend toward more ecological applications, the RSPS suite provides capabilities for very explicit support of commercial business operations in forest management.

Woodstock is the strategic model-building component of RSPS, and provides the core functionality upon which the other components build. Woodstock provides a generic modeling framework within which user-defined models can be specified to address almost any type of land management problem. Modeling solutions are obtained by simulation, optimization, or a combination of the two methods. Typical applications might include any of the following objectives:

- Sustainable management of wood supply, habitat, biodiversity, watershed management, and other forest values.

- Management to meet forest certification criteria.
- Design and evaluation of harvest schedules and treatment regimes.
- Evaluation of economic efficiencies such as present net value.

The Allocation Optimizer component provides resource planners and managers with a tool to develop and assess strategies that allocate wood products to markets by considering wood supply origins, product transportation costs, delivered wood product prices, destination demands, and inventory capacity. Typical applications of this component include:

- Assessing multiple strategies for allocating wood fiber.
- Assessing open-market wood purchase strategies.
- Maximizing total revenue by allocating products to destinations.
- Minimizing haul costs by associating treatment decisions with transportation costs.
- Identifying wood production bottlenecks.
- Identifying future wood supply problems for existing mills.
- Exploring the consequences of adding or closing a mill.

The Spatial Woodstock component supports management and analysis of spatial data. It functions as a map viewer and data manager for viewing, reporting, and analyzing results from the other three system components. A basic objective underlying this component is the ability to represent knowledge about spatial relationships that can help assess the operational feasibility of plans. For example, insights gained from mapping the locations of current and future management activities can be fed back into Woodstock and Stanley (discussed next) to develop more operationally feasible plans.

The final RSPS component, Stanley, is used to build and schedule spatial harvest units, conditioned by specifications in the strategic Woodstock plan. Stanley provides a transition to the operational level by automatically blocking and spatially scheduling all aspects of a management plan. Blocking and scheduling is accomplished by aggregating forest polygons into harvest units subject to minimum and maximum constraints on block size and other spatial constraints and decision criteria established in the Woodstock strategic management plan.

7. RELATIONS BETWEEN DECISION TOOLS AND OTHER TECHNOLOGIES

Up to this point, we have presented software systems for decision making more or less in isolation. However, as the scope of chapter topics in this book should make clear, numerous types of computer-based applications are now being brought to bear to support (usually) specific facets of sustainable forest management. An understanding of how each class of application

contributes to supporting sustainable forest management is certainly a valuable starting point for forestry practitioners, and this, indeed, is a major goal of this book. However, as Shao and Reynolds (Chapter 1) discuss, it is at least as important for practitioners to understand how the various classes of applications can be employed collaboratively to achieve the broader objective of implementing sustainable for management.

So, how can computer-aided decision making fit in with, or complement, other types of computer applications? First, and perhaps most obviously, many of the technologies discussed in this book are designed to support landscape characterization (Chapters 2 and 3), and, as such, may provide the raw data and information on which a decision-support application operates. In some cases, a decision-support application may operate directly on this raw information, but in many cases the input required is some form of statistical summary provided by applications such as those discussed in Chapters 5, 6, 7, and 9. In either case, there is a flow of information from some other computer-based applications to the decision-support application.

Unfortunately, it has not often been appreciated that information flow in the reverse direction can be at least as valuable, especially with respect to improving implementation efficiency for processes such as adaptive management (Maser et al. 1994). Too often, groups of natural-resource experts have prescribed data requirements, for landscape assessment for example, on an *a priori* basis, with no formal analysis of how the data to be collected will be evaluated to answer the questions posed by the problem at hand. Such approaches to data requirements can result in either failing to recognize the need for critical information until late in the overall process, or collecting information that is never used. On the other hand, use of computer-aided decision tools early in management processes such as landscape assessment has the potential to achieve significant efficiencies by formally mapping relations between questions to be answered, states and processes that need to be considered, and data (Reynolds 2001a, 2001b). The result is better tailored data collection, which may reduce costs and will help ensure that the information collected is commensurate with the decisions that one expects to make.

8. FUTURE DEVELOPMENTS

Having reviewed an array of contemporary technologies in this chapter that support decision making, it seems appropriate to conclude by speculating a little on the direction of further developments in the near future. Of course, predicting the future is always a rather risky proposition, so we will avoid

being overly specific, and instead consider what seem to be three major cross-cutting trends that apply more or less generically.

8.1 Internet-based implementation

The Internet already has opened up interesting possibilities for real-time collaborative application development. With the advent of powerful Internet-meeting services in the past few years, it is now relatively easy for a diverse group of geographically dispersed experts, perhaps representing various disciplines relevant to some issue in sustainable forestry for example, to collaborate on the design of a DSS application. Most contemporary DSS are still run by individuals working on desktop computers, so it is worth noting that the desktop-development environment is not necessarily a serious constraint in this context. Indeed, the authors have worked with a number of groups over the past few years, collaboratively developing desktop applications by means of Internet-meeting services. However, new technological advances continue to open up new, perhaps even more promising, possibilities.

The past few years have seen a steady migration of decision-support technologies to internet-based implementations, in which applications can be run or even developed online (e.g., a simplified forest vegetation simulator called 4S-Tool, <http://www.purdue.edu/apps/forestry/4STool>). At least a few of the systems described in this chapter, for example, now offer internet-based versions. The trend toward such solutions is likely to continue because this mode of delivery has some clear advantages to software developers in terms of system maintenance and obviating the need for distribution and associated support services.

There are potential benefits to user communities as well. In particular, there is the real potential for improved access to advanced software systems among users in developing countries because they can purchase an analytical service on an as-needed basis rather than purchasing the system outright, which might be prohibitively expensive. Also, Internet applications often have few limitations on which hardware or software (e.g., operating system) the end-user must have available.

An Internet-based implementation is also accessible anywhere and anytime, as long as an Internet connection exists, rather than traditional software installations on a limited number of computers. In addition to, or instead of, online development of applications, some newer systems now provide the ability to export analysis products to the internet for broad dissemination. Given the strong emphasis on so-called e-Government initiatives in the United States and other developed countries, this Internet-based trend is very likely to continue.

8.2 Systems integration versus collaboration

Over the past few decades, computer-based aids to decision making have been increasing in number as well as in their sophistication with respect to the scope and complexity of problems that they can handle. Significant advances often have been achieved through integration of different functions, some examples of which were discussed in section 6. However, systems integration is not always necessarily the best solution, at least initially.

Many of the systems now available could be considered complementary to one another, but each is typically a complex system in its own right, so that the creation of new hybrid systems out of two or more independent ones is usually not trivial, and can be a complex, slow, and expensive proposition. The case for systems integration may seem compelling for specific combinations of systems, but, rather than rush too quickly into a program of integration, a better short-term approach may be to test integration concepts by operating the systems independently, but collaboratively. In effect, this approach amounts to simulating how the integrated system should operate.

In contrast to the foregoing discussion in this section, newer software design concepts such as those based on Component Object Models (COM) and semi-autonomous agents (e.g., NED) have opened up possibilities that have been facilitating systems integration, particularly in the last decade. Recent advances in the implementation of EMDS version 3.0 (section 6), for example, were facilitated by COM. Many current decision systems could be described as legacy systems insofar as their design predates standards such as COM. However, as platform-independent technologies such as .Net, Simple Object Access Protocol (SOAP), and Extensible Markup Language (XML) are increasingly adopted for new systems development, or for redesign of existing systems, opportunities for relatively easy systems integration as well as migration to Internet implementations (section 8.1) are likely to continue increasing as well.

8.3 Accommodating the human dimension

The evolution of computer aids to decision making has been largely driven by advances in technology (Ekbja and Reynolds, in press), and most systems have been developed to support a rational model of decision making in the sense of Mintzberg et al. (1976). However, in recent years, social scientists, working in the field of decision theory, have been advancing new approaches, based on concepts such as collaborative or mutual learning (Daniels and Walker 1996), dialectic approaches (Elgarah et al. 2002), social DSS (Turoff et al. 2002), and similar ideas. Most of the new approaches

focus on decision support in a group or public context, which is certainly appropriate, considering that the problems being addressed today are often large and complex, requiring the collaboration of many specialists, and are often played out in very public settings.

Because single individuals rarely make natural resource management decisions, group decision making has become a priority topic—at least in the MCDM community—but applying equally well to the broader DSS arena. Empirically, we have come to understand that group decisions are typically better than average individual performance, but rarely as good as the best individual. Hence, while there are many other reasons to engage groups in decision processes, consistently making the best decision choices is not one of them. Reasons for participatory decision making include: broad ownership in the decisions and their implications, support for implementation of decisions, more complete coverage of all pertinent issues and viewpoints during the decision process, and the appearance of an open and inclusive decision process. There are numerous examples of research and case studies on group-based DSS for forestry and natural resource management (*q.v.*, Schmoldt et al. 2001, Rauscher *et al.* in press). Given the growing importance of inclusive and open decision processes in forestry, it is reasonable to assume that participatory decision making will continue to generate new developments in DSS. The movement toward Internet-based DSS implementations opens up greater possibilities to engage decision makers at dispersed locations through virtual meeting environments; these currently include such things as group whiteboards, document and application sharing, audio/video connectivity, voting, and Delphi processes. For DSS that operate at multiple scales, decisions made at a regional level could then be handed down and incorporated into multiple, subregional decision-making processes. But, instead of regional decisions being policy mandates as is currently done, regional decisions would transparently filter down to tactical and operational decision making at the finer scales, through the DSS. This has broad implications for organizational decision making and how tightly an organization couples that activity with DSS tools.

There has been a strong tendency to present the new approaches as alternatives to the rational approach on the grounds that the latter is unworkable in the context of managing ecosystems and sustainable forest management. It may be more constructive, however, to explore the proposition that rationality is a necessary, but not sufficient, condition for decision making in the new context of forest management. Consider that a basic definition of rational is simply, “able to be reasoned about.” We find it difficult to imagine how the new approaches can succeed if there is not a rational core to the decision process by which the multiple alternative views can be rendered mutually understandable, providing a foundation for

constructive dialogue. Ekbia and Reynolds (in press) explore these ideas further, and demonstrate how rational models and the newer concepts from decision science can complement each other in decision-making processes.

Much more research into this area will be required to make significant progress, but this line of inquiry also may prove to be one of the most profitable for advancing the application of computer-aided decision making in the next several years.

ACKNOWLEDGMENTS

We thank the staff of Remsoft for their assistance with describing the Woodstock family of products.

REFERENCES

- Allen, T.F.H., and Starr, T.B., 1982, *Hierarchy: Perspectives for Ecological Complexity*, University of Chicago Press, Chicago.
- Anonymous, [no date]. *Spectrum overview*, U.S. Department of Agriculture, Forest Service, Inventory and Monitoring Institute, Fort Collins, CO.
- Arrue, B., Ollero, A., and Dios, J., 2000, An intelligent system for false alarm reduction in infrared forest-fire detection, *IEEE Intelligent Systems* 5: 64-73.
- Blackard, J., and Dean, D., 1999, Comparative accuracies of artificial neural networks and discriminant analysis in predicting forest cover types from cartographic variables, *Computers and Electronics in Agriculture* 24: 131-151.
- Booch, G., 1994, *Object-oriented Analysis and Design with Applications*, Benjamin/Cummings, New York.
- Buchanan, B.G., and Shortliffe, E.H. (eds.), 1984, *Rule-Based Expert Systems: The MYCIN Experiments of the Stanford Heuristic Programming Project*, Addison-Wesley, Reading, MA.
- Buech, R.R., Martin, C.J., and Rauscher, H.M., 1989, An application of expert systems in wildlife: forest stand prescription advisors for deer and grouse, *AI Applications in Natural Resource Management* 41: 3-10.
- Crookston, N.L., 1997, Suppose: an interface to the Forest Vegetation Simulator, in: *Proceedings of the Forest Vegetation Simulator Conference*, R. Teck, M.Moeur, and J. Adams, eds., 3-7 February 1997, Fort Collins, CO, Gen. Tech. Rep. INT-GTR-373, U.S. Department of Agriculture, Forest Service, Intermountain Research Station, Ogden, UT, pp. 7-14.
- Daniels, S.E., and Walker, G.B., 1996, Collaborative learning: Improving public deliberation in ecosystem-based management, *Environmental Impact Assessment Review* 16: 71-102.
- Davis, L.S., Johnson, K.N., Bettinger, P.S., and Howrad, T.E., 2001, *Forest Management to Sustain Ecological, Economic, and Social Values*, Fourth Edition, McGraw-Hill, Boston, Massachusetts.
- Drechsler, M., 2004, Model-based conservation decision aiding in the presence of goal conflicts and uncertainty, *Biodiversity and Conservation* 13: 141-164.

- Duda, R.O., and Gaschnig, J.G., 1981, Knowledge-base expert systems come of age, *BYTE* 6: 238-281.
- Durkin, J., 1993, *Expert Systems: Catalog of Applications*, Intelligent Computer Systems, Inc., Akron, OH.
- Edwards, W., 1977, How to use multi-attribute utility measurement for social decision making, *IEEE Transactions on Systems, Man, and Cybernetics* 7: 326-340.
- Edwards, W., and Newman, J.R., 1982, *Multi-attribute Evaluation*, Sage, Beverly Hills, CA.
- Ekbja, H.R., and Reynolds, K.M., in press, Decision support for sustainable forestry: enhancing the rational model, in: *Sustainable Forestry in Theory and Practice*, K.M. Reynolds, A. Thomson, M. Köhl, M. Shannon, D. Ray, and K. Rennolls, eds., CABI Publishing, Wallingford, UK.
- Elgarah, W., Courtney, J.F., and Haynes, J.D., 2002, A dialectical methodology for decision support systems design, in: *Proceedings of the 35th Annual Hawaii International Conference on System Sciences, Big Island, Hawaii*, pp. 198-210.
- Ellison, A.M., 1996, An introduction to Bayesian inference for ecological research and environmental decision-making, *Ecological Applications* 6: 1036-1046.
- Ellison, A.M., 2004, Bayesian inference in ecology, *Ecological Letters* 7: 509-520.
- Feigenbaum, E.A., 1977, The art of artificial intelligence: themes and case studies in knowledge engineering, *International Journal of Computing and Artificial Intelligence* 5: 1014-1029.
- Gershon, M., Duckstein, L., and McAniff, R., 1982, Multiobjective river basin planning with qualitative criteria, *Water Resources Research* 18: 193-202.
- Giarratano, C.J., and Riley, G.D., 1998, *Expert Systems: Principles and Programming*, Cole Publishing, Three Lakes, WI.
- Gigerenzer, G., and Todd, P.M., 1999, *Simple Heuristics that Make Us Smart*, Oxford University Press, Oxford.
- Gustafson, E., Nestler, J., Gross, L., Reynolds, K., Yaussy, D., Maxwell, T., and Dale, V., 2003, Evolving approaches and technologies to enhance the role of ecological modeling in decision-making, in: *Advances in Ecological Modeling*, V. Dale, ed., Springer-Verlag, New York, pp. 135-164.
- Halpern, D.F., 1989, *Thought and Knowledge: An Introduction to Critical Thinking*, Lawrence Erlbaum Associates, Hillsdale, New Jersey.
- Hester, A.S., Hann, D.W., and Larsen, D.R., 1987, *ORGANON User Manual: Southwest Oregon Growth and Yield Model*, Oregon State University, Corvallis, OR.
- Hill, M.J., Braaten, R., Veitch, S.M., Lees, B.G., and Sharma, S., 2005, Multi-criteria decision analysis in spatial decision support: the ASSESS analytic hierarchy process and the role of quantitative methods and spatially explicit analysis, *Environmental Modelling and Software* 20: 955-976.
- Holling, C.S., 1978, *Adaptive Environmental Assessment and Management*, John Wiley and Sons, London.
- Holsapple, C.W., 2003, Decision support systems, in: *Encyclopedia of information systems, Volume I*, H. Bidgoli, ed., Academic Press, New York, pp. 551-565.
- Howard, R., and Matheson, J., 1981, Influence diagrams, in: *Readings on the Principles and Applications of Decision Analysis*, R. Howard, and J. Matheson, eds., Strategic Decisions Group, Menlo Park, CA. pp. 721-762.
- Iverson, D.C., and Alston, R.M., 1986, *The Genesis of FORPLAN: a Historical and Analytical Review of Forest Service Planning Models*, U.S. Department of Agriculture, Forest Service, General Technical Report INT-214, Intermountain Forest and Range Experiment Station, Ogden, Utah.

- Jackson, P., 1990, *Introduction to Expert Systems*, Addison-Wesley Publishers, Reading, Massachusetts.
- Johnson, K.N., 1980, *Forest Planning Model (FORPLAN): Users Guide and Operations Manual*, U.S. Department of Agriculture, Forest Service, Washington, DC.
- Johnson, K.N., 1987, *FORPLAN Version 2: Mathematical Programmer's Guide*, U.S. Department of Agriculture, Forest Service, Washington, DC.
- Kamenetzky, R., 1982, The relationship between the analytical hierarchy process and the additive value function, *Decision Sciences* 13: 702-716.
- Kaufmann, A., 1975, *Introduction to the Theory of Fuzzy Subsets, Volume 1, Fundamental Theoretical Elements*, Academic Press, New York.
- Keeney, R.L., and Raiffa, H., 1976, *Decisions with Multiple Objectives*, Wiley, New York.
- Klein, M., and Methlie, L.B., 1990, *Expert Systems: A Decision Support Approach*, Addison-Wesley, Reading, MA.
- Leskinen, P., Kangas, J., and Pasanen, A., 2003, Assessing ecological values with dependent explanatory variables in multi-criteria forest ecosystem management, *Ecological Modeling* 170: 1-12.
- Levy, J.K., Hipel, K.W., and Kilgour, D.M., 2000, Using environmental indicators to quantify the robustness of policy alternatives to uncertainty, *Ecological Modeling* 130: 79-86.
- Lexer, M.J., 2000, A multi-attribute utility model for silvicultural decision-making in secondary Norway spruce forests, *Forstwissenschaftliches Centralblatt* 119: 377-394.
- Liu, C., Zhang, L., Davis, C., Solomon, D., Brann T., and Caldwell, L., 2003, Comparison of neural networks and statistical methods in classification of ecological habitats using FIA data, *Forest Science* 49: 619-631.
- Maes, P., 1991, *Designing Autonomous Agents: Theory and Practice from Biology to Engineering and Back*, MIT Press, Cambridge, MA.
- Maser, C., Bormann, B.T., Brookes, M.H., Kiester, A.R., and Weigand, J.F., 1994, Sustainable forestry through adaptive ecosystem management is an open-ended experiment, in: *Sustainable Forestry: Philosophy, Science, and Economics*, C. Maser, (ed.). St. Lucie Press, Delray Beach, Florida, pp. 303-340.
- McGaughey, R., 1997, Visualizing forest stand dynamics using the stand visualization system. *Proceedings of the 1997 ACSM/ASPRS Annual Convention and Exposition*, April 1997, Seattle, WA, American Society for Photogrammetry and Remote Sensing, Bethesda, MD, pp. 248-257.
- Miller, B.J., and Saunders, M.C., 2002, *The NetWeaver Reference Manual*. Pennsylvania State University, College Park, PA.
- Mintzberg, H., Raisinghani, D., and Theoret, A., 1976, The structure of unstructured decision processes, *Administrative Science Quarterly* 21: 246-275.
- Nii, H.P., 1989, Blackboard systems, in: *Artificial Intelligence*, Volume IV, A. Barr, P.R. Cohen, and E.A. Feigenbaum, (eds.), Addison-Wesley Publishing, Reading, MA, pp. 3-82.
- Nute, D., Rosenberg, G., Nath, S., Verma, B., Rauscher, H.M., Twery, M.J., and Grove, M., 2000, Goals and goal orientation in decision support systems for ecosystem management, *Computers and Electronics in Agriculture* 27: 355-375.
- O'Toole, R., 1983, *A Citizens' Guide to FORPLAN*, Cascade Holistic Economy Consultants, Eugene, Oregon.
- Peng, C., and Wen, X., 1999, Recent applications of artificial neural networks in forest resource management: an overview, in: *Environmental Decision Support Systems and Artificial Intelligence*, Technical Report WS-99-07, U. Corté and M. Sánchez-Marré (eds.), AAAI Press, Menlo Park, CA, pp. 15-22.

- Potter, W.D., Liu, S., Deng, X. and Rauscher, H.M., 2000, Using DCOM to support interoperability in forest ecosystem management decision support systems, *Computers and Electronics in Agriculture* 27: 195-226.
- Prato, T., 1999, Multiple attribute decision analysis for ecosystem management, *Ecological Economics* 30: 207-222.
- Rauscher, H.M., 1999, Ecosystem management decision support for federal forests in the United States: a review, *Forest Ecology and Management* 114: 173-197.
- Rauscher, H.M., and Reynolds, K.M., 2003, Information systems in natural resource management, in: *The Encyclopedia of Information Systems*, Volume 3, H. Bidgoli, ed., Academic Press, New York, pp. 239-265.
- Rauscher, H.M., Benzie, J.W., and Alm, A.M., 1990, A red pine forest management advisory system: knowledge model and implementation, *AI Applications in Natural Resource Management* 4: 27-43.
- Rauscher, H.M., Schmoltdt, D.L., and Vacik, H., in press, Information and knowledge management in support of sustainable forestry: a review, in: *Sustainable Forestry in Theory and Practice*, K. Reynolds, A. Thomson, M. Köhl, S. Shannon, D. Ray, and K. Rennolls, eds., CABI Publishing, Cambridge, MA.
- Remsoft. 2005, About the Remsoft spatial planning system, in: *Allocation Optimizer User Guide*, Remsoft Inc., Fredericton, New Brunswick, pp. 9-14.
- Reynolds, K.M., 2001a, Using a logic framework to assess forest ecosystem sustainability. *Journal of Forestry* 99: 26-30.
- Reynolds, K.M., 2001b, *Fuzzy Logic Knowledge Bases in Integrated Landscape Assessment: Examples and Possibilities*, Gen. Tech. Rep. PNW-GTR-521, U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station, Portland, OR.
- Reynolds, K.M., 2005, Integrated decision support for sustainable forest management in the United States: fact or fiction?, *Computers and Electronics in Agriculture* 49: 6-23.
- Reynolds, K.M., and Holsten, E.H., 1997, *SBexpert Users Guide (version 2.0): A Knowledge-Based Decision-Support System for Spruce Beetle Management*, PNW-GTR-401, U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station, Portland, OR.
- Reynolds, K.M., Rodriguez, S., and Bevans, K., 2003a, *User Guide for the Ecosystem Management Decision Support System, Version 3.0*, Environmental Systems Research Institute, Redlands, California.
- Reynolds, K.M., Johnson, K.N., and Gordon, S.N., 2003b, The science/policy interface in logic-based evaluation of forest ecosystem sustainability, *Forest Policy and Economics* 5: 433-446.
- Romero, C., and Rehman, T., 2003, *Multiple Criteria Analysis for Agricultural Decisions*, 2nd ed., Elsevier, Amsterdam, Holland.
- Saaty, T.L., 1977, A scaling method for priorities in hierarchical structures, *Journal of Mathematical Psychology* 15: 234-281.
- Schmoltdt, D.L., 1987, *Evaluation of an Expert System Approach to Forest Pest Management of Red Pine (Pinus resinosa)*, Ph. D. dissertation, University Microfilms International, University of Wisconsin-Madison, Madison WI, USA.
- Schmoltdt, D., 2001, Application of artificial intelligence to risk analysis in forest management, in: *Risk Analysis in Forest Management, Managing Forest Ecosystems*, vol. 2, K. von Gadow, ed., Kluwer Academic Publishers, New York, pp. 49-74.
- Schmoltdt, D.L., and Martin, G.L., 1986, Expert systems in forestry: utilizing information and expertise for decision making, *Computers and Electronic in Agriculture* 1: 233-250.

- Schmoldt, D.L., and Martin, G.L., 1989, Construction and evaluation of an expert system for pest diagnosis of red pine in Wisconsin, *Forest Science* 35: 364-387.
- Schmoldt, D.L., and Rauscher, H.M., 1996, *Building Knowledge-Based Systems for Natural Resource Management*, Chapman & Hall, New York.
- Schmoldt, D.L., Kangas, J., Mendoza, G.A., and Pesonen, M. (eds.), 2001, *The Analytic Hierarchy Process in Natural Resources and Environmental Decision Making*, Kluwer Academic Publishers, Dordrecht.
- Schmoldt, D.L., Li, P., and Abbott, A.L., 1997, Machine vision using artificial neural networks and 3D pixel neighborhoods, *Computers and Electronics in Agriculture* 16: 255-271.
- Schuster, E.G., Leefers, L.A., and Thompson, J.E., 1993, *A Guide to Computer-Based Analytical Tools for Implementing National Forest Plans*, Gen. Tech. Rep. INT-296, U.S. Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station, Moscow, ID.
- Stewart, T.J., 1992, A critical survey on the status of multiple criteria decision making theory and practice, *Omega* 20: 569-586.
- Stone, N.D., Coulson, R.N., Frisbie, R.E., and Loh, D.K., 1986, Expert systems in entomology: three approaches to problem solving, *Bulletin of the Entomological Society of America* 32: 161-66.
- Turban, E., and Aronson, J., 2004, *Decision Support Systems and Intelligent Systems*, 7th ed., Prentice-Hall, New York.
- Turoff, M., Hiltz, S.R., Cho, H.-K., Li, Z. and Wang, Y., 2002, Social decision support systems, in: *Proceedings of the 35th Annual Hawaii International Conference on System Sciences*, Big Island, Hawaii, pp. 211-219.
- Twery, M.J., Rauscher, H.M., Knopp, P.D., Thomasma, S.A., Nute, D.E., Potter, W.D., Maier, F., Wang, J., Dass, M., Uchiyama, H., and Glende, A., 2005, NED-2: an integrated forest ecosystem management decision support system, *Computers and Electronics in Agriculture* 49: 24-43.
- von Winterfeldt, D., and Edwards, W., 1986, *Decision Analysis and Behavioral Research*, Cambridge University Press, Cambridge.
- Walters, J.C., 1986, *Adaptive Management of Renewable Resources*, Macmillan, New York.
- Walters, J.C., and Holling, C.S., 1990, Large-scale management experiments and learning by doing, *Ecology* 71: 2060-2068.
- Wasserman, P.D., 1989, *Neural Computing: Theory and Practice*, Van Nostrand Reinhold, New York.
- Waterman, D.A., 1986, *A Guide to Expert Systems*, Addison-Wesley Publishers, Reading, Massachusetts.
- Winston, P.H., 1977, *Artificial Intelligence*, Addison-Wesley, Reading, MA.
- Wolfslehner, B., Vacik, H., and Lexer, M.J., 2005, Integrating network analysis to a framework for evaluating sustainable forest management, *Forest Ecology and Management* 207: 157-170.
- Zadeh, L.A., 1965, Fuzzy sets, *Information and Control* 8: 338-353.
- Zadeh, L.A., 1968, Probability measures of fuzzy events, *Journal of Mathematical Analysis and Application* 23: 421-427.
- Zadeh, L.A., 1975a, The concept of a linguistic variable and its application to approximate reasoning, part I, *Information Science* 8: 199-249.
- Zadeh, L.A., 1975b, The concept of a linguistic variable and its application to approximate reasoning, part II, *Information Science* 8: 301-357.

- Zadeh, L.A., 1976, The concept of a linguistic variable and its application to approximate reasoning, part III, *Information Science* 9: 43-80.
- Zhang, G., 2000, Neural networks for classification: a survey, *IEEE Transactions on Systems, Man and Cybernetics* 30: 451-462.