Fuzzy Logic Knowledge Bases in Integrated Landscape Assessment: Examples and Possibilities

Keith M. Reynolds

Author

Keith M. Reynolds is a research forester, Forestry Sciences Laboratory, 3200 SW Jefferson Way, Corvallis, OR 97331.

Abstract

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The literature on ecosystem management has articulated the need for integration across disciplines and spatial scales, but convincing demonstrations of integrated analysis to support ecosystem management are lacking. This paper focuses on integrated ecological assessment because ecosystem management fundamentally is concerned with integrated management, which presupposes integrated analysis. Knowledge-based solutions are particularly relevant to ecosystem management because the topic is conceptually broad and complex and involves many abstract concepts whose assessment depends on many interdependent states and processes. Logic constructs are useful in this context because the problem can be evaluated as long as the entities and their logical relations are understood in a general way and can be expressed by subject matter authorities. As an example, ecosystem management decision-support system provides a formal logic framework for integrated analysis across multiple problem domains, has the ability to reason with incomplete information, and assists with optimizing the conduct of assessments by setting priorities on missing data. Most significant, however, is the possibility that knowledge-based reasoning could readily be extended to networks of knowledge bases that provide logical specifications for integrated analysis across spatial scales.

Keywords: Knowledge base, fuzzy logic, hierarchy, network, integration, ecosystem management, ecological assessment, landscape analysis.
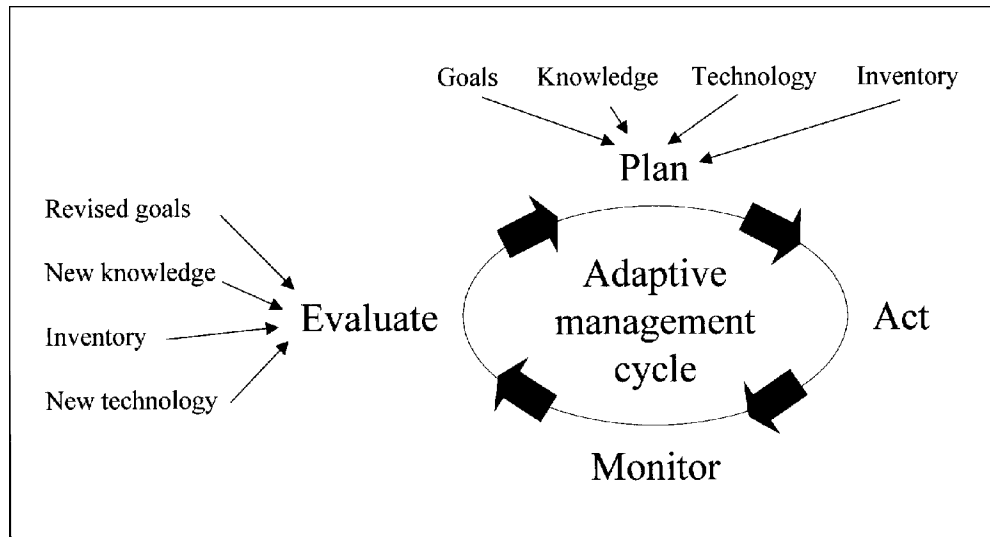
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Figure 1—The adaptive ecosystem management process (adapted from Maser et al. 1994).

Introduction

Ecological assessment is fundamental to ecosystem management, which has emerged as a basic principle of natural resource management in the United States since the 1990s (Committee of Scientists 1999). Ecosystem management has been defined as "…the use of skill and care in handling integrated units of organisms and their environments… to produce desired resource values, uses, or services in ways that also sustain the diversity and productivity of ecosystems" (Overbay 1993, p. 5). The primary goal of ecosystem management is ecosystem sustainability (Daly and Cobb 1989, Dixon and Fallon 1989, Gale and Cordray 1991, Greber and Johnson 1991, Maser 1994), which in its broadest sense means achieving an operational balance among concerns for ecological states and processes, economic feasibility of management actions, and social acceptability of expected management consequences (Bormann et al. 1994, Salwasser 1993).

Conceptual models for an adaptive ecosystem management process have been proposed (fig. 1) as ways to implement ecosystem management (FEMAT 1993, Maser et al. 1994). The process is conceived as a continuous cycle that includes monitoring, assessment (evaluation in fig. 1), planning, and implementation. A process that actively supports adaptation is necessary because ecosystems are complex entities and our knowledge about them is limited. In addition, both the social and biophysical components of ecosystems are highly dynamic and unpredictable. Ecological assessment is fundamental to ecosystem management because it simultaneously is the concluding step of an iteration on the cycle and generates revisions to current knowledge that become the basis for adaptation in the next iteration (Committee of Scientists 1999).

This paper focuses on integrated ecological assessment because ecosystem management fundamentally is concerned with integrated management, which presupposes integrated analysis. The literature on ecosystem management indicates the need for integration across disciplines and spatial scales. However, convincing

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demonstrations of integrated analysis to support ecosystem management have been lacking. This paper discusses practical approaches to integrated assessment across disciplines and spatial scales, landscape-level application of the latter, and near-term prospects for extending the approaches to embrace much of the full adaptive management process.

Current Approaches to Ecosystem Assessment

Several broad-scale ecoregional assessments have been conducted in the United States in recent years (Anon. 1996, 1997; Everett et al. 1994; FEMAT 1993), and several more are in progress. Each assessment has used a now well-standardized approach to define the analytical problem. A scoping process was used to identify and evaluate critical issues deserving consideration. A needs assessment was performed to identify data requirements and analytical methods needed to respond to the issues. Various statistical, simulation, and optimization procedures have been used to address various components of the overall assessment problem. To assert that analyses used in these assessments were conducted ad hoc would be a disservice. However, although assessment teams may have carefully coordinated the conduct of analyses with integration in mind, there is little evidence in the reports that effectively integrated analysis was achieved.

Improving Integration in Assessments with Knowledge-Based Reasoning

Expert systems (Jackson 1990, Waterman 1986), known more generically as knowledge-base systems (Waterman 1986), began to appear in significant numbers in natural resource management in 1983 (Davis and Clark 1989). More recently, Durkin (1993) catalogued over 100 knowledge-base applications in the environmental sciences. O'Keefe (1985) envisioned an important role for knowledge-base systems as components of larger decision-support systems in the future.

A knowledge base is a formal logical specification for interpreting information and is therefore a form of metadatabase in the strict sense. A knowledge base is a logical representation of a problem in terms of relevant entities in the problem domain and logical relations among them. Interpretation of data by a knowledge-base engine provides an assessment of system states and processes represented in the knowledge base as topical entities. Use of logical representation for assessing the state of systems frequently is desirable or necessary. Often, the current state of knowledge about a problem domain is too imprecise for statistical or simulation models or optimization, each of which presume precise knowledge about relevant mathematical relations. In contrast, knowledge-based reasoning provides solutions for evaluating more imprecise information.

Adaptation and Limitations

Knowledge-based solutions are particularly relevant to ecosystem management because the topic is conceptually broad and complex and involves many, often abstract, concepts (e.g., health, sustainability, ecosystem resilience, ecosystem stability, etc.) whose assessment depends on many interdependent states and processes. Logical constructs are useful in this context because the problem can be evaluated as long as the entities and their logical relations are understood in a general way and can be expressed by subject matter authorities.

Logic-based analysis is not in direct competition with other, more traditional forms of analysis. Instead, knowledge-based representations can be used as logical frameworks within which results from many specific mathematical models are integrated.

Traditional knowledge-based systems, dating from the early 1970s, have used rule-based reasoning. Such systems conventionally have only been suitable for narrow, well-defined problems (Jackson 1990, Waterman 1986). As discussed in the next section, however, newer forms of knowledge-based representation, based on object models and fuzzy logic, substantially improve the ability to model large, general problem domains such as ecosystem assessment.

A New Approach to Ecosystem Assessment

The USDA Forest Service, Pacific Northwest Research Station released the first production version of the ecosystem management decision-support (EMDS) system in February 1997. The EMDS system integrates a knowledge-base engine into the ArcView GIS (Environmental Systems Research Institute) [1] to provide knowledge-based reasoning for landscape-level ecological analyses. As of November 1999, about 325 sites worldwide have requested EMDS, including about 60 USDA Forest Service sites, 125 national research institutes, and another 110 universities. The implications of this new hybrid technology are examined from several points of view.

Object-Based Logic Networks for Problem Specification

NetWeaver was initially developed in 1988, based on concepts originally proposed by Stone et al. (1986). It has steadily evolved since and now provides a substantially different form of knowledge representation that offers several advantages over production-rule systems that make it highly suitable for landscape-level ecosystem analyses. Key features of the system include an intuitive graphical user interface, object-based logic networks of propositions, and fuzzy logic. Implementation of the user interface together with NetWeaver's object-based representation supports design of highly modular knowledge bases. Modularity in turn enables effective, incremental evolution of knowledge-base structures from simple to complex forms. Modern systems theory asserts that incremental evolution is a virtual requirement for design of complex systems (Gall 1986).

Fuzzy Logic and Compact Representation

Fuzzy logic representations are more intuitively satisfying than classical Boolean (bivalent) logic, as well as more precise and compact compared to classical rule-based representations. Zadeh (1965, 1968) first presented basic concepts of approximate reasoning with fuzzy logic. Subsequent concept papers (Zadeh 1975a, 1975b, 1976) elaborated on the syntax and semantics of linguistic variables, laying the foundation for what has now become a significant branch of applied mathematics. Fuzzy logic is concerned with quantification of set membership and associated set operations. Formally (Kaufmann 1975),

> let E be a set, denumerable or not, and let $\times$ be an element of E. Then a fuzzy subset A of E is a set of ordered pairs $\{\times, \mu_A(\times)\}$, $\times \quad E$, in which $\mu_A(\times)$ is a membership function that takes its values from the set $M = [0, 1]$, and specifies the degree of membership of $\times$ in A.

Because fuzzy set theory is a generalization of Boolean set theory, most Boolean set operations have equivalent operations in fuzzy subsets (Kaufmann 1975, p. 11).

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[1] 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.

Application of fuzzy logic to natural resource science and management is still relatively new. General areas of application include classification in remote sensing (Blonda et al. 1996), environmental risk assessment (Holland 1994), phytosociology (Moraczewski 1993a, 1993b), geography (Openshaw 1996), ecosystem research (Salski and Sperlbaum 1991), and environmental assessment (Smith 1995, 1997). More specific applications include catchment modeling (Anon. 1994), cloud classification (Baum et al. 1997), evaluation of plant nutrient supply (Hahn et al. 1995), soil interpretation (Mays et al. 1997, McBratney and Odeh 1997), and land suitability for crop production (Ranst et al. 1996).

To appreciate the compactness of fuzzy set representation versus bivalent logic in production-rule systems, consider the following example. Suppose that risk of a landslide depends on three factors, A, B, and C. Rather than simply concluding that risk is true, we want to refine our conclusion to selection from among the outcomes risk.low, risk.mod, risk.high, and risk.extreme. If each factor also has a rating of low, moderate, high, or very high, then there are potentially 256 rules that at least need to be considered. The number of rules tends to increase combinatorially. With a large number of discrete rules, the potential for logical incompleteness also is very high. This is a small example. Reflection on the relative complexity of the example versus that of the ecosystem management domain should make it clear how impractical bivalent reasoning becomes in the context of large problems.

Now consider the fuzzy logic implementation of the same landslide risk problem. In NetWeaver, each factor is represented by a data object, each having an associated fuzzy membership function. Risk is evaluated by a single network object that contains a graphically constructed logic expression, typically involving a limited number of combinations of the three data objects. In the simplest case, for example, the NetWeaver representation of the risk problem would require one network object with a single logical expression to evaluate the three data objects. A more complex formulation might require a single network object with a compound logical expression involving multiple references to the three data objects, and with each elementary expression using varying combinations of fuzzy arguments on the data objects. Even in this more complex case, there would still only be one network object, three data objects (because they are reusable by multiple reference), and now perhaps six to nine fuzzy arguments.

Similarly, fuzzy logic has significant practical advantages over Bayesian belief networks (Ellison 1996, Howard and Matheson 1981) in some contexts. Bayesian belief networks may be preferable to fuzzy logic networks when conditional probabilities of outcomes are known. However, Bayesian belief networks, like production rule systems, are difficult to apply to large, general problems because the number of conditional probabilities that must be specified can quickly become extremely large as the conceptual scope of a problem increases. In such situations, model design not only becomes difficult to manage but many probabilities will not be well characterized and will therefore need to be supplied by expert judgment, thus negating much of the value to be gained by a more statistically based approach to knowledge representation.

This argument is not meant to imply that fuzzy logic networks are inherently superior to Bayesian belief networks or other forms of knowledge representation. On the contrary, the alternative forms of representation just discussed may be highly complementary to one another in practice. In particular, fuzzy logic networks are well suited as logic frameworks for integrating model results from various analytical systems such as simulators, linear programs, Bayesian belief networks, and production-rule systems.

Integration Across Disciplines

Problem specification for ecological assessment may well deserve to be classified as a "wicked problem" (Allen and Gould 1986). As discussed in the introduction, ecosystem assessment must consider many states and processes of biophysical, social, and economic components of an ecosystem. Many entities may have both deep and broad networks of logical dependencies as well as complex interconnections. Although constructing such complex representations in NetWeaver is not trivial, it is at least rendered feasible by the precision and compactness of fuzzy logic relations, and by the graphic, object-based representation of logic networks in the system interface. No subject-matter authority, nor for that matter any group of authorities, is capable of holding a comprehensive cognitive map of such a complex problem domain in their consciousness. On the other hand, the graphic, object-based form of knowledge representation in NetWeaver is highly conducive to the incremental evolution of knowledge-base design from simple to complex forms.

Landscape Implementation

Major components of the EMDS system include the NetWeaver knowledge-base system, the EMDS Arcview application extension, and the Assessment system (fig. 2). This section briefly summarizes system structure and function in terms of system-level objects and their methods and relations. More detailed descriptions of the system are provided in Reynolds et al. (1996, 1997a, 1997b) and Reynolds (1999a).

The NetWeaver knowledge-base system (Reynolds 1999b) is composed of an engine and a graphic user interface for knowledge-base developers that provide controls for designing, editing, and interactively evaluating knowledge bases (fig. 2). Primary components of the EMDS Arcview application extension are the DataEngine and MapDisplay objects that customize the Arcview environment with methods and data structures required to integrate NetWeaver's knowledge-based reasoning schema into Arcview. The Assessment system is a graphic user interface to the NetWeaver engine for end-users of the EMDS application that controls setup and running of analyses, runtime editing of knowledge bases, and display of maps, tables, graphs, and evaluated knowledge-base state related to analyses.
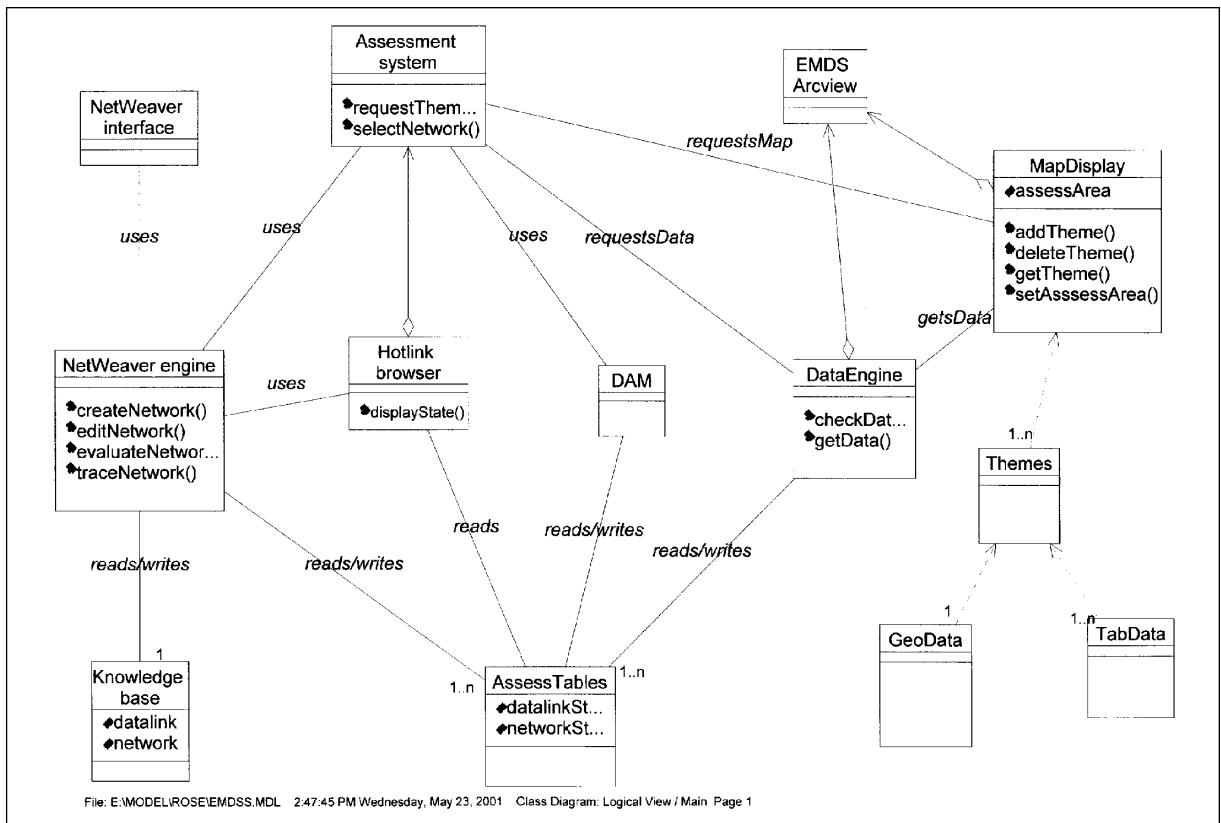
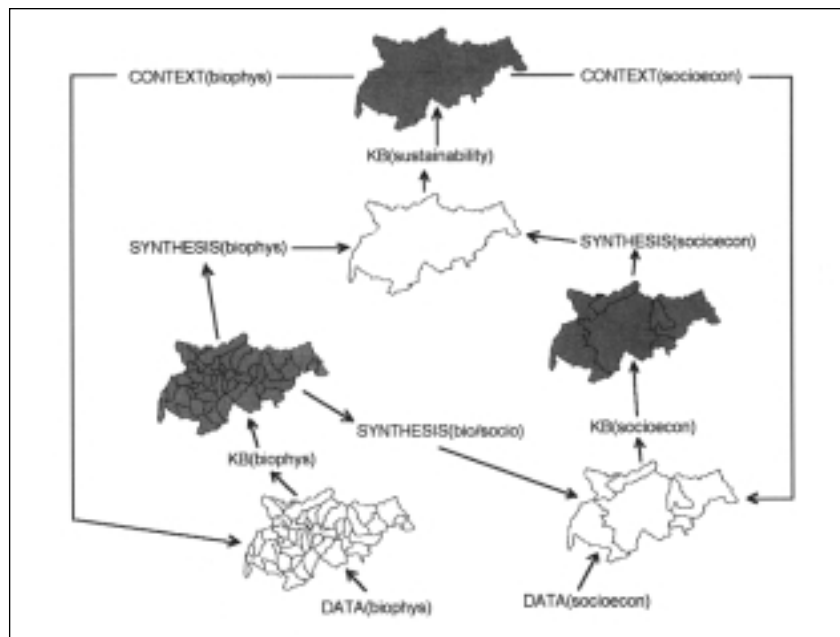Figure 2—Object diagram of the ecosystem management decision-support system.

Figure 3—Knowledge-based integration across scales.

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Integration Across Spatial Scales

It is relatively easy in principle to extend integrated analysis via knowledge-based reasoning over multiple spatial scales (fig. 3). Data from fine-scale landscape features such as watersheds are first processed by a knowledge base designed for that scale. Knowledge-base output, shown as evaluated states in the middle of the figure, then go through an intermediate filter (typically implemented in a spreadsheet or database application) to synthesize information for input to the next coarser scale. A second knowledge base processes the synthesized information to provide an assessment of landscape attributes at the top of the figure. Finally, knowledge base outputs at the broader landscape scale may feed back to the fine scale as context information that influences evaluations at the fine scale. This simple conceptual model (fig. 3) provides the basis for a formal logical specification of analyses that is consistent across scales. Hierarchies, or even networks, of knowledge-based analyses as suggested would be highly consonant with ecosystem theories concerning the hierarchical organization of ecosystems (Allen and Starr 1982).

Practical Advantages for Landscape Assessment

Discussion thus far already has alluded to some practical advantages to integrating knowledge-based reasoning into a GIS system, including use of logical frameworks for integrating knowledge over numerous and diverse problem domains. This section considers three additional advantages that are more specifically associated with use of the NetWeaver engine in EMDS.

Evaluation with Incomplete Information

In the future, assessment teams may be able to assemble a list of all topics they want to include in an assessment, as well as a list of data requirements needed to address those topics, and find they have all the requisite data. At present, however, assessments routinely start with incomplete data. There may be some missing observations or no data for several to many data types. One solution to the problem of missing data is to limit the scope of analyses to those topics for which data already exist or can be easily acquired. Tailoring analyses to suit existing data is undesirable because the assessment becomes driven by the data at hand rather than the questions that are really of interest. Moreover, acquiring missing data usually is both time-consuming and expensive. Even if there is no conscious decision to limit the conduct of analyses to existing data, it may be difficult to avoid subconscious rationalization.
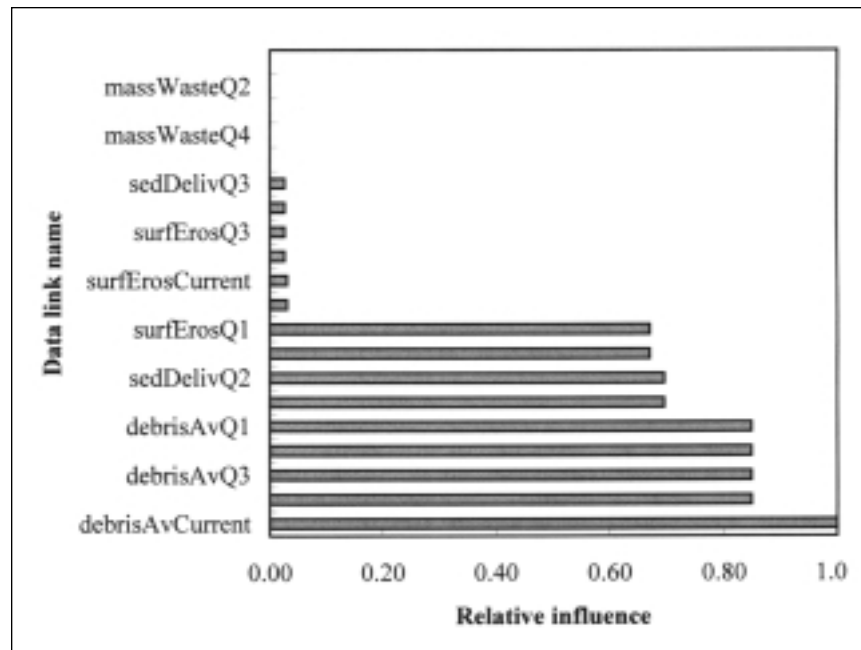
Figure 4—Evaluation of the influence of missing data in the ecosystem management decision-support system.

NetWeaver was chosen as the inference engine for EMDS primarily because it supports robust analyses under conditions of missing data. Recall from the earlier discussion that NetWeaver implements a fuzzy propositional logic. NetWeaver also could be described as an evidence-based reasoning system; propositions of network objects are neutral to missing data, and whatever data are available incrementally contributes to, or detracts from, the strength of evidence supporting a proposition. In NetWeaver, influence of data is computed as a function of the number of times a data object is referenced with the knowledge-base structure, and the level(s) at which the data enter. The EMDS system computes synoptic measures of influence that also account for the number of records in which a data field has missing values.

Influence of Missing Data on Completeness of an Assessment

The influence of missing data is closely related to the ability to reason with incomplete information. Influence, in this context, refers to the degree to which missing data would contribute to completeness of an assessment. The NetWeaver inference engine uses simple rules to compute influence, based on how many states and processes use the information and at which levels the missing information would enter a knowledge-base structure (Reynolds 1999b). The Data Acquisition Manager of EMDS (Reynolds 1999a, DAM in fig. 2) uses synoptic information about data influence to assist EMDS users with prioritizing new data acquisition needs (fig. 4). The ability to compute influence and set priorities for collecting data is particularly useful owing to the highly dynamic nature of data influence. Due to interdependencies between data, influence not only depends on which fields in a database are populated but also on the values in those fields (Reynolds et al. 1997b).
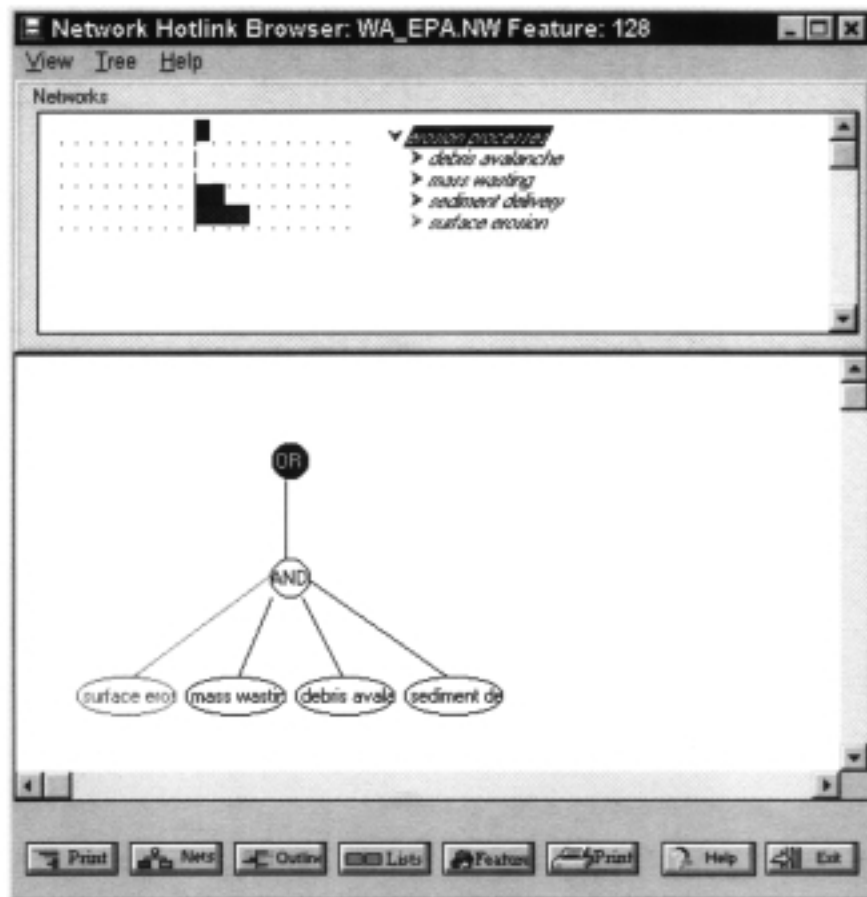
Figure 5—Graphic display of evaluated knowledge-base state for a selected landscape
feature in an ecosystem management decision-support system analysis.

Interpretation   Logic structures in the domain of ecological analysis and assessment can be highly
complex owing to potentially large numbers of logical entities and their interrelations.
The NetWeaver hotlink browser in EMDS (fig. 2) has a NetWeaverlike interface that
displays an expandable outline view of the evaluated knowledge base as well as the
evaluated state of networks selected in the outline (Reynolds 1999a, fig. 5). Whereas
the graphic interface of NetWeaver is useful for knowledge-base testing and valida-
tion in the NetWeaver development environment, the graphic interface of the hotlink
browser in EMDS facilitates tracing the underlying logic that leads to observed states
in a relatively intuitive manner.

Table 1—Primary networks in the knowledge base for assessing watershed condition

Network name	Proposition evaluated by network
Watershed processes:	Watershed processes are within acceptable ranges.
Hydrologic processes	Hydrologic processes in the watershed are within acceptable ranges compared to reference conditions (table 2).
Erosion processes	Erosion processes in the watershed are within an acceptable range compared to reference conditions (table 2).
Fire processes	Fire processes in the watershed are in good condition compared to reference conditions (table 2).
Watershed patterns:	Watershed patterns are within acceptable ranges
Upland patterns	Upland patterns in the watershed are within acceptable ranges compared to reference condition. Evaluation includes vegetation composition and structure.
Valley bottom patterns	Valley bottom processes in the watershed are within acceptable ranges compared to reference conditions. Evaluation includes vegetation composition and structure, stream type composition, sinuosity, woody debris, pool frequency, bank stability, and sediment transport capacity.
Channel patterns	Channel characteristics in the watershed within acceptable ranges compared to reference conditions. Evaluation includes bankfull width to depth ratio, pool depth, flood-plain width, and fines in riffles.
Human influence	Aggregate effects of human influence are within acceptable ranges compared to management standards. Evaluation includes effects of roads, dams, diversions, channelization, groundwater extraction, mines, grazing, and recreation.
Aquatic species:	Likelihood of long-term viability of aquatic species is good.
Fish habitat	Fish habitat potential in watershed is good. Evaluation includes effects of baseflow, substrate, water temperature, and cover.

Examples of Current EMDS Applications

Several knowledge-base development projects are underway at the Pacific Northwest Research Station and Pennsylvania State University. Initial efforts are focusing on integrated analysis for specific spatial scales. Progress to date provides strong evidence that it is feasible to construct NetWeaver knowledge bases for ecosystem management despite the conceptual scope and complexity of the problem domain. A few example prototype knowledge bases have been completed in the past 12 months.

Assessment of Hydrologic Integrity

Reynolds et al. (1999) designed a knowledge base for assessment of watershed-level hydrologic integrity for the U.S. Environmental Protection Agency. Primary logic networks for assessing integrity are **watershed processes**, **watershed patterns**, **human influence**, and **aquatic species**. Each network evaluates a specific proposition about the state of watershed condition (table 1). A simplified hierarchy of the logic structure under the network for watershed processes illustrates the scope of the watershed processes topic (table 2). Topic structure (table 2) has been simplified for brevity by omission of intermediate calculated data links and terminal data links.

We trace the logic structure from **watershed processes** (fig. 6) down to **total yield** (figs. 7-11) as a typical example of knowledge-base structure. The truth value for the proposition that watershed processes are within suitable ranges of conditions depends on the degree to which the premises, or logical antecedents, of watershed processes are true (fig. 6). The logic structure of the network (fig. 6) makes the meaning of the proposition (table 2) explicit. The network for **hydrologic processes** (fig. 7) similarly has logically antecedent conditions, represented by networks, that determine the truth of its proposition (table 2). The *AND* nodes (figs. 6 and 7) are fuzzy logic operators. In conventional fuzzy logic, an AND operation is implemented mathematically as a min function over the set of logical antecedents, x_i (Kaufman 1975). However, the NetWeaver implementation of *AND* is a minimum-biased weighted average of its logical antecedents expressed as

$$AND = x_{min} + (\overline{x} - x_{min})(x_{min} + 1)/2 ,$$

in which $x_{min} = min(x_i, i=1,.., n)$, and $\overline{x}$ is the weighted average of the x_i. Other logic operators in NetWeaver include *OR*, *SOR*, *XOR*, and *NOT* (table 3).

Determination of suitable hydrologic processes depends, among other things (table 2), on suitable stream flow (figs. 8 and 9). Evaluation of the **stream flow** network depends on the evaluation of four other networks (table 2), but whereas the network for **hydrologic processes** is evaluated by a fuzzy *AND* expression (fig. 7), stream flow is evaluated by calculating a sum of products in the calculated data link **stream flow sum calc** (fig. 9). The difference in formulations is semantically significant. The computation of **stream flow sum calc** and its use in the fuzzy node in the **stream flow** network (fig. 8) effectively asserts that networks contributing to evaluation of **stream flow** can compensate for one another to some extent. If, for example, the network for **total yield** evaluates to completely false, but some other network, say **peak flow**, evaluates to completely true, then **peak flow** at least partially compensates for **total yield**. The **stream flow** network also is typical of many networks in the knowledge base in its use of weights that are read as data for weighting the importance of networks contributing to evaluation of **stream flow** (fig. 9).

Table 2—Propositions associated with networks antecedent to the watershed processes network

Network name	Proposition	Source of comparison[a]
Hydrologic processes:	Hydrologic processes are within suitable ranges.	--
Stream flow—	Stream flow characteristics are within suitable ranges.	--
Total yield	Total water yield is within a suitable range.	Reference
Peak flow	Peak flow is within a suitable range.	Reference
Base flow	Base flow is within a suitable range.	Reference
Bankfull discharge	Bankfull discharge is within a suitable range.	Reference
Water quality—	Attributes of water quality are within suitable ranges.	--
Sediment--	Sediment attributes are within a suitable range.	--
Bedload	Bedload is within a suitable range.	Reference
Dissolved solids	Concentration of dissolved solids is within a suitable range.	Reference
Suspended solids	Concentration of suspended solids is within a suitable range.	Reference
Coliform	Coliform count is within a suitable range.	Regulation
Dissolved O_2	Concentration of dissolved oxygen is within a suitable range.	Regulation
Water temp—	Water temperature characteristics are within suitable ranges.	--
Temp max	7-day running average for summer maximum water temperature is within a suitable range.	Regulation
Temp thresh	Number of days that daily maximum water temperature exceeds threshold is within a suitable range.	Regulation
Nutrients—	Nutrient concentrations are within suitable ranges.	--
Nitrogen concn	Nitrogen concentration is within a suitable range.	Regulation
Phosphorous concn	Phosphorous concentration is within a suitable range.	Regulation
Metals—	Metal concentrations are within suitable ranges of regulatory requirements.	--
Aluminum concn	Aluminum concentration is within a suitable range.	Regulation
Arsenic concn	Arsenic concentration is within a suitable range.	Regulation
Copper concn	Copper concentration is within a suitable range.	Regulation

Table 2—Propositions associated with networks antecedent to the watershed processes network (continued)

Network name	Proposition	Source of comparison[a]
Mercury concn	Mercury concentration is within a suitable range.	Regulation
Zinc concn	Zinc concentration is within a suitable range.	Regulation
Erosion processes:	Erosion processes are within suitable ranges.	--
Surface erosion	Amount of surface erosion is within a suitable range.	Reference
Mass wasting	Amount of mass wasting is within a suitable range.	Reference
Debris avalanche	Amount of debris avalanche is within a suitable range.	Reference
Sediment delivery	Amount of sediment delivery is within a suitable range.	Reference
Fire processes:	Fire processes are within suitable ranges.	--
Fire frequency	Fire frequency is within a suitable range.	Reference
Fire hazard	Amount of expected fire damage is within a suitable range.	Reference

[a] Observed data values are compared to fuzzy membership functions, representing either reference conditions or regulatory requirements, to determine if an observed value falls within a suitable range of values. Data defining fuzzy membership functions for reference conditions and regulatory requirements are read by the knowledge base to parameterize the fuzzy membership function.
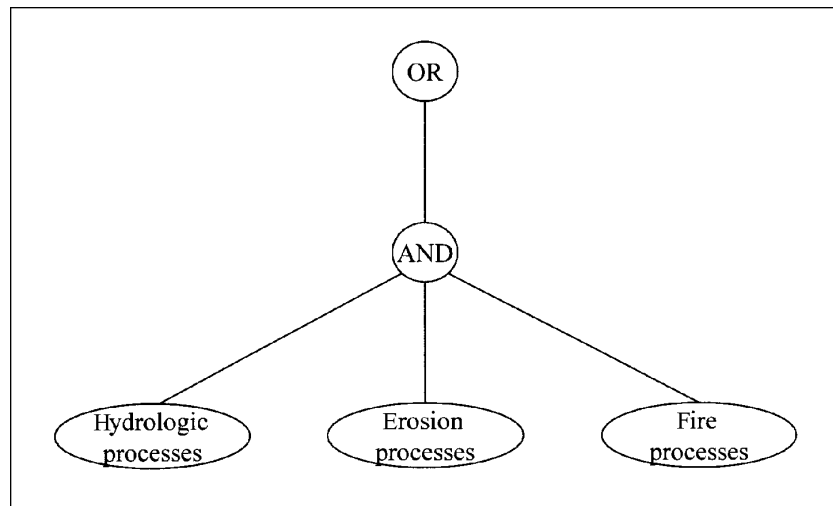
Figure 6—Network for **watershed processes**. The truth of the proposition that watershed processes are within a suitable range of conditions depends on the degree to which its three premises, represented by the networks **hydrologic processes**, **erosion processes**, and **fire processes**, are true.
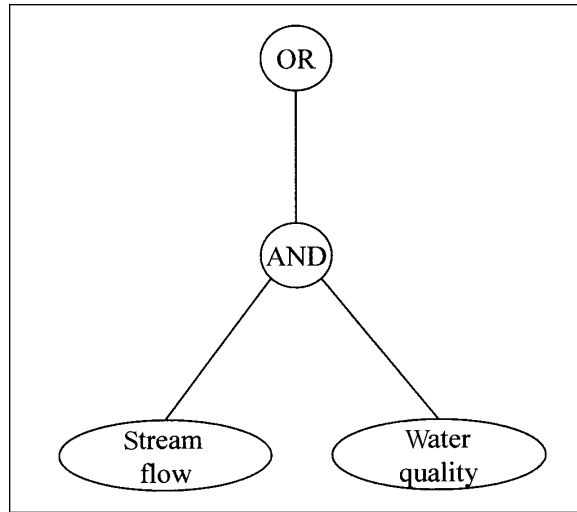
Figure 7—Network for **hydrologic processes**. The truth of
the proposition that hydrologic processes are within a suit-
able range of conditions depends on the degree to which its
two premises, represented by the networks **stream flow**,
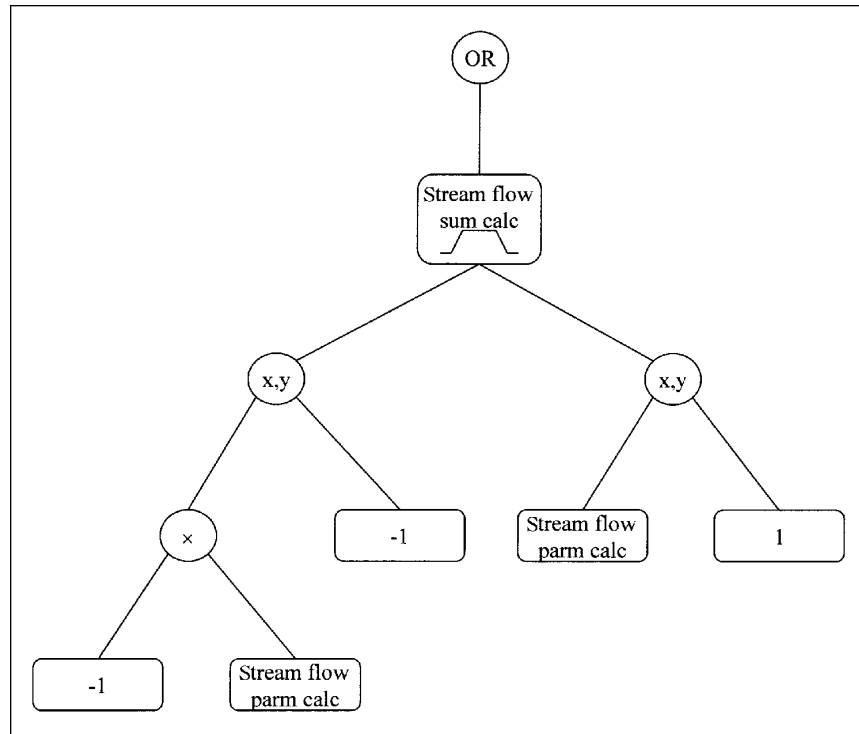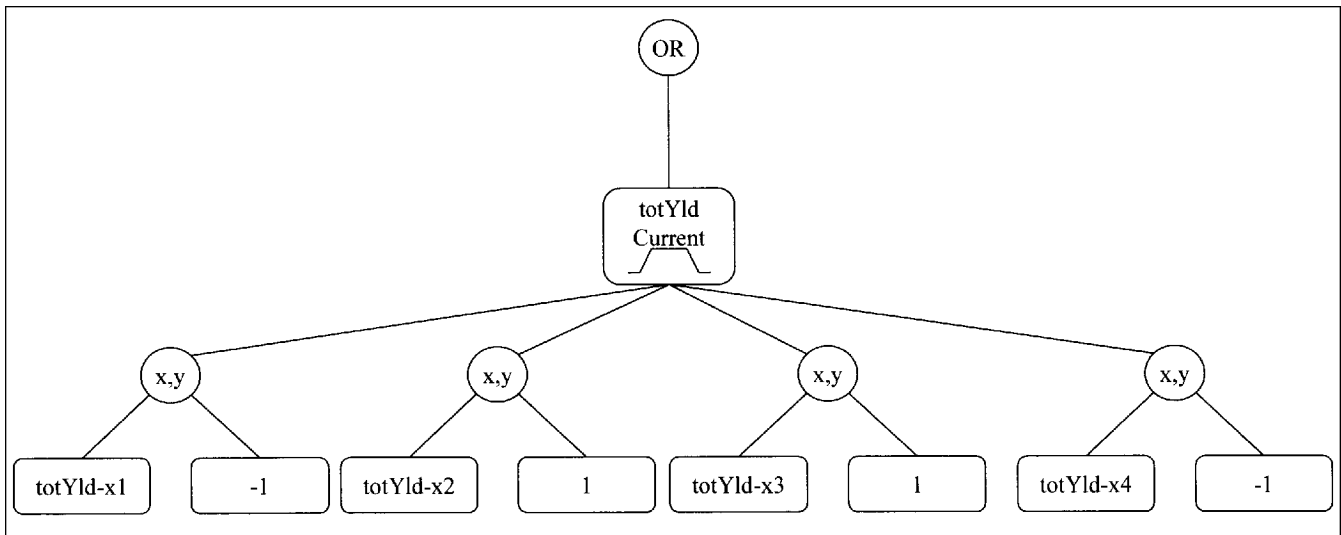and **water quality**, are true.

Figure 8—Network for **stream flow**. The rounded box represents a fuzzy curve that is
dynamically defined. The fuzzy curve object compares the value of **stream flow sum
calc** (fig. 9) to the x coordinates in its xy nodes to interpolate the truth value for **stream
flow**. The calculated data link, stream flow   calc, computes the sum of the weights for
terms in fig. 9 to dynamically define the x coordinates of the xy nodes.

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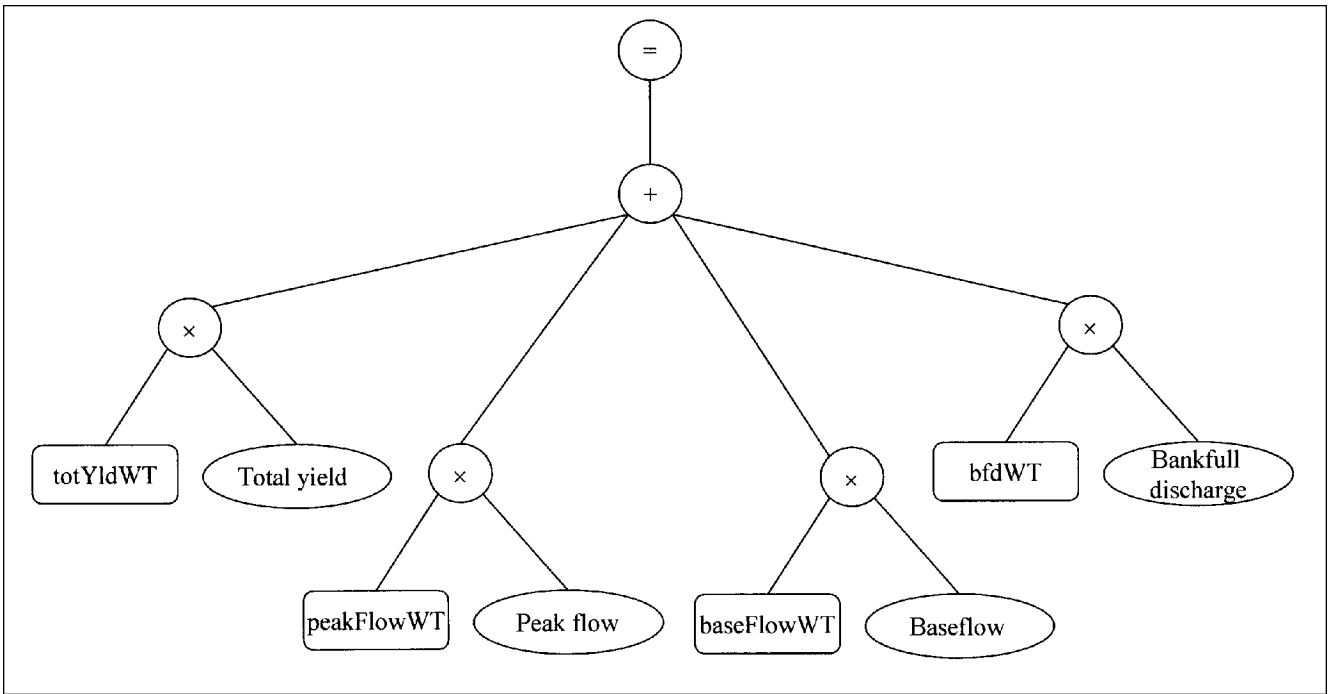
Figure 9—Calculated data link for stream flow sum calculation. The calculated data link computes a sum of products. The weights for each term in the sum are read as data.

Figure 10—Network for **total water yield** from the watershed. The rounded box represents a fuzzy curve that is dynamically defined. The fuzzy curve object compares the value of **totYldCurrent** to the x coordinates in its xy nodes to interpolate the truth value for **total yield**. The x terms in each xy node are calculated data links (fig. 11).
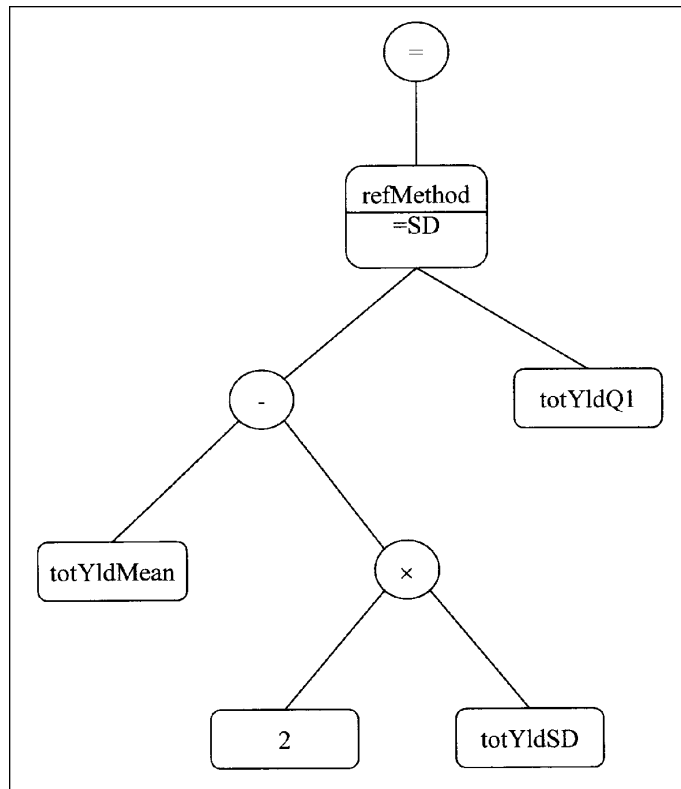
Figure 11—X terms for xy nodes (fig. 10) are either computed from the mean and standard deviation (read as data) or computed as quantiles (read as data).

Table 3—NetWeaver logic operators

Operator	Type	Truth value returned
AND	Set	Minimum-biased weighted average of the truth values of its logical antecedents.
NOT	Unary	Negation of the truth value of its antecedent.
OR	Set	Maximum truth value in the set of its logical antecedents.
SOR	Set	Truth value of the first logical path (ordered left to right) with sufficient data.
XOR	Set	Logical distance between its two most true logical antecedents.
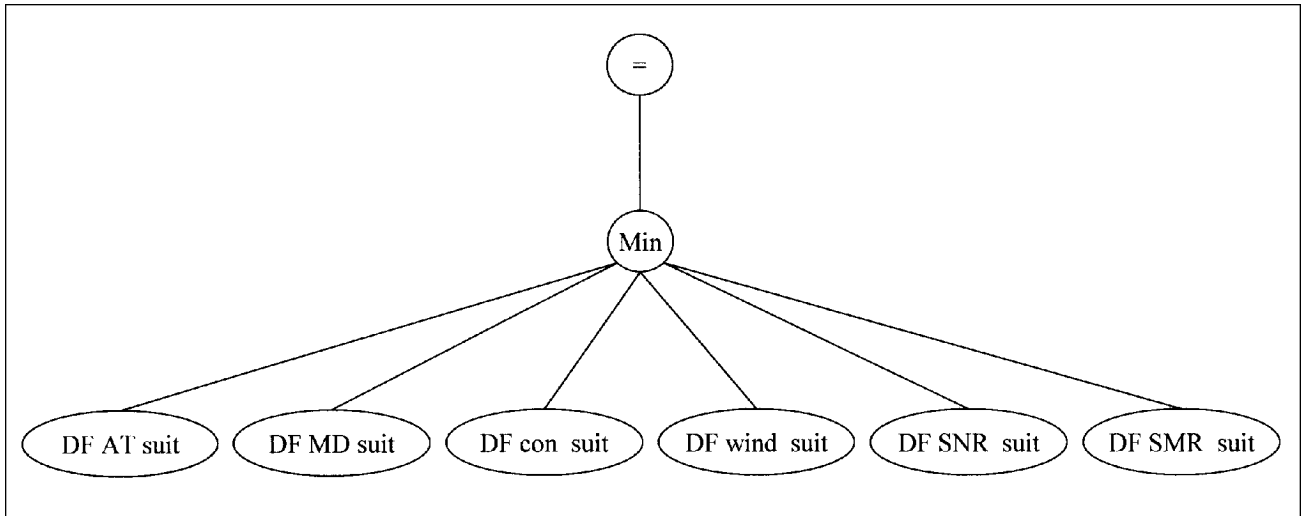
Figure 12—Network for evaluation of ecological site suitability of Douglas-fir in Great Britain. **AT, MD, con, wind, SNR** and **SMR suit** indicate logic networks that evaluate site suitabilities for accumulative air temperature, moisture deficit, continentality, wind, soil nutrient regime, and soil moisture regime, respectively, with respect to Douglas-fir.
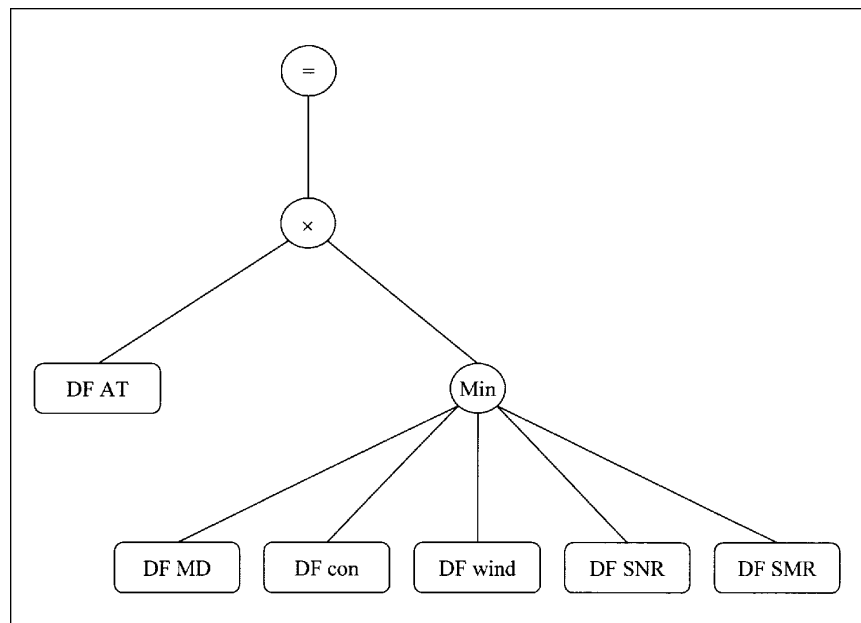

Figure 13—Network for evaluating yield suitability of Douglas-fir in Great Britain. **AT, MD, con, wind, SNR** and **SMR** indicate computational networks that compute site indices for accumulative air temperature, moisture deficit, continentality, wind, soil nutrient regime, and soil moisture regime, respectively, for Douglas-fir.

Total yield (fig. 10) is typical of all terminal (that is, lowest level) networks in the knowledge-base hierarchy (table 2) in that it evaluates a simple data link to get the current condition (**totYldCurrent** in this case) and compares this value to a dynamically defined fuzzy membership function that specifies a suitable reference condition for total water yield. *XY* nodes under the fuzzy curve object (fig. 10) define the shape of the fuzzy membership function. The form of the curve for **total yield** also is typical of most dynamically defined fuzzy membership functions for all terminal networks in the knowledge base; *y* terms are constants and *x* terms are computed from data. With a few exceptions, *x* terms are evaluated by calculated data links in which a switch object is used to select one of two methods for computing *x* (fig. 11). *X* is computed from the mean and standard deviation (totYldMean and totYldSD, respectively, in fig. 11) of a reference condition if the data value of **refMethod** = SD, or x is assigned a quantile value (e.g., **totYldQ1** in fig. 11).

Ecological Site Classification

Ray et al. (1998) designed a knowledge base for ecological site classification (ESC) that evaluates site suitability of commercial tree species for the reforestation program of the British Forestry Commission. Each species has a network that evaluates ecological suitability (fig. 13) and a network that evaluates yield suitability (fig. 13). Ecological suitability is determined by the most limiting environmental condition (fig. 13), whereas yield suitability is determined as the product of realized growth potential based on accumulative air temperature (**AT**) and the most limiting of other factors (fig. 13).

The knowledge base was developed as a literal translation of the ESC expert system (Ray et al. 1996). The current version is somewhat unusual for NetWeaver knowledge bases insofar as computations are primarily numeric rather than logic-based. Nevertheless, the NetWeaver implementation has been considered highly successful owing to both conversion of categorical outcomes to continuous indices based on fuzzy logic, and to the ability of EMDS to process hundreds of forest management units in a single analysis.[2] Ray and colleagues plan continued development of the current prototype, including assessment of ecological suitability for 20 native woodland types and addition of topics related to evaluation of biodiversity and sustainability. Both lines of enhancement are expected to rely more heavily on logic-based processing.

Forest Ecosystem Sustainability

One of the major accomplishments of the 1992 Earth Summit (Rio de Janeiro, Brazil) was the enunciation of a set of principles for sustainable development of the world's forest resources (United Nations 1992). Subsequently, signatory nations to the 1995 Santiago Declaration, representing about 90 percent of the world's boreal and temperate forest cover, affirmed the recommendations of the Montreal Process that prescribed a set of seven criteria and 67 indicators for evaluating forest ecosystem sustainability. The specifications of the Montreal Process are notable in two respects. First, the specifications provide relatively clear definitions of ecosystem

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[2] Ray, D. 1998. Personal communication. Soil scientist, British Forestry Commission, Forest Research, Roslin, Midlothian, Scotland, UK.

attributes requiring evaluation. Second, however, the Montreal Process does not prescribe the manner in which criteria and indicators are to be interpreted to draw conclusions about the state of forest ecosystem sustainability. Additional specifications that enable consistent interpretations of monitoring data on sustainability clearly would be useful.

In 1999, I designed a prototype knowledge base for comprehensive evaluation of all Montreal criteria and indicators (Reynolds 2000). The knowledge base contains two complementary, primary logic networks; the first evaluates current conditions in relation to long-term desired future conditions, and the second evaluates trend by comparing conditions between the current and a past assessment. As with the knowledge base for hydrologic integrity, all fuzzy membership functions in the knowledge base for the Montreal prototype are dynamically defined. Thus, the logic specification for evaluation of forest ecosystem sustainability is extremely general and could be applied to any country or major bioregion. Readers are referred to Reynolds (2000) for additional details of the specification because the knowledge base is extremely large.

Conclusions

Awareness of the value of fuzzy logic for environmental analysis has been increasing in the natural resource science community over the past 7 to 8 years. Increased attention to the possible benefits of fuzzy logic-based approaches to analysis and assessment has paralleled shifts in systems analysis from relatively narrow, well-defined problems such as harvest schedule optimization to much larger, more poorly defined problems such as maintaining ecosystem health. Note Zadeh's (1975a,1975b) early thoughts on this:

> *…the ineffectiveness of computers in dealing with [biological] systems is a manifestation of what might be called the principle of incompatibility—a principle which asserts that high precision is incompatible with high complexity. Thus, it may well be the case that the conventional techniques of system analysis and computer simulation…are intrinsically incapable of coming to grips with the great complexity of human thought processes and decision-making. …Indeed, it is entirely possible that only through the use of [approximate reasoning] could computer simulation become truly effective as a tool for the analysis of systems which are too complex or too ill-defined for the application of conventional quantitative techniques.*

Zadeh's (1975a, 1975b) comments on complexity seem no less compelling today than when first published nearly 25 years ago. Indeed, if anything, organi-zations and individuals who have had to confront the complexities of ecosystem assessment over the past 8 to 9 years should probably have a keener appreciation for Zadeh's (1975a,1975b) remarks than his contemporaries at the time.

Integration of the NetWeaver knowledge-base engine into a GIS environment, as described for the current version of EMDS, is not the ultimate solution to ecosystem management and ecological assessment; it does suggest, however, some promising possibilities for continued evolution of knowledge-based systems in landscape analysis. As a starting point, EMDS provides a formal logic framework for integrated analysis across multiple problem domains, has the ability to reason with incomplete information, and assists with optimizing the conduct of assessments by setting priorities on missing data. Perhaps most significantly, however, was the relatively recent insight that the advantages of knowledge-based reasoning could readily be extended to logic networks of knowledge bases that provide logic specifications for integrated analysis across spatial scales.

Author's Note

EMDS version 2.0 for ArcView 3.2 is currently available from the download page of the EMDS website (www.fsl.orst.edu/emds). EMDS version 3.0 for ArcGIS 8.1 will be available at the same site beginning about December 1, 2001. Requests for CDs of either version also can be submitted from the download page.

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