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Use of Expert Systems in Wildlife-Habitat Modeling

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Abstract.—The next phase of modeling wildlife-habitat relationships may involve use of expert systems technology. An expert system is a computer program that reasons like a human expert to solve such problems as diagnosis and classification. A wildlife-habitat expert system may predict response of wildlife species to habitat conditions and changes and may use probabilistic structures of program control and computation. Two demonstration programs (BRUSH and GUILD) illustrate such predictions by using "data-driven" reasoning, program explanations of its reasoning process, and capabilities for suggesting habitat-management prescriptions. Existing computer programs that help create and maintain expert systems may reduce model development time by an order of magnitude. Questions of utility, audience, cost, peer review, and validation require careful scrutiny. Other factors may include deciding which human experts to model the reasoning process after and selecting appropriate problems for expert system formalism.

Predicting the response of wildlife species to habitat conditions (vegetation type and successional stage) and changes in conditions is the goal of many wildlife managers and land-use planners. Currently, data storage and retrieval systems (e.g., Patton 1978; Marcot 1980; Verner 1980) and models that index habitat capability, such as those of the U.S. Fish and Wildlife Service (Schamberger et al. 1982) and USDA Forest Service (Hurley et al. 1982), are being developed and used.

A next generation of predictive modeling may extend these approaches by using computers to integrate information from field studies, the literature, and expert opinion. Computer software engineering that would aid in predicting the response of species to habitat conditions is known as expert systems engineering. An expert system is a computer-based consultation program consisting of facts and expert knowledge to help classify, diagnose, or plan (Duda and Shortliffe 1983). The use of currently available data storage and retrieval systems and habitat-capability models requires the user to ask all pertinent questions and develop lines of reasoning, whereas with expert systems the computer conducts much of the querying and reasoning by using built-in rules. In this chapter I review expert systems technology, present two demonstration models, discuss expert performance and the use of expert systems to build knowledge bases, and present guidelines and cautions for the possible next generation of wildlife-habitat models.

Expert systems technology: A brief review

An expert system is a computer program that uses facts and "if-then" choices or rules to solve a problem in technology or management. Specifically, expert systems may be used in problems of classification, such as classifying chematographic profiles or habitat conditions, or diagnosis, such as diagnosing patients' symptoms or habitat suitability for wildlife species. Hundreds of such rules may be combined into what is termed "rule networks." The expert system transcends traditional data storage and retrieval programs in its ability to keep track of its own reasoning process, to handle uncertainty and rules of thumb in computations, and to revise its own data base and logic structure from experience. Expert systems aimed at practical application often reach performance levels comparable to those of a human expert in some specialized problem domains (Nau 1983).

Expert system programs have been used to assist in the diagnosis of medical symptoms (MYCIN; Shortliffe 1976), in the interpretation of mass spectroscopy (DENDRAL; Lindsay et al. 1980), and in the design of computer hardware configuration (R1; McDermott 1982). A consulting system for mineral exploration, PROSPECTOR (Duda and Shortliffe 1983), has successfully located new mineral deposits. Duda and Shortliffe (1983), Hayes-Roth et al. (1983), and Nau (1983) have reviewed other system applications. None of the existing applications, however, has addressed problems in ecology or wildlife management.

An expert system consists of two integrated parts: a knowledge base and a logic control structure, sometimes referred to as an "inference engine" (Brachman et al. 1983). A knowledge base is a coded list of fundamental facts and a set of rules for using the facts under different contexts. Facts may be represented as relations, such as "Natal roosts of hoary bats = Dense tree foliage." Rules may be represented as if-then syllogisms, such as shown in Figure 23.1. (Note the use of a probability statement in line 3850, rule R11.)

The inference engine is a set of controls consisting of general problem-solving knowledge (Buchanan et al. 1983). An inference engine is essentially the logic structure of program execution. One example of a high-level control rule may be to execute a particular subset of facts and rules that pertain to deducing species' use of deciduous foliage in a forest

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3630 REM
3640 REM   ****** RULES FOR DEDUCTIVE INFERENCE ******
3650 REM
3660 DATA  "BRUSHFIELD"
3670 DATA  "R1", "IF", "HAS <20% WOODY VEGETATION COVER", "THEN", "IS GRASS STAGE"
3680 DATA  "R2", "IF", "CONTAINS >5% COVER BULL THISTLE", "THEN", "IS GRASS STAGE"
3690 DATA  "R3", "IF", "HAS MOST SHRUBS <2 M TALL", "THEN", "IS EARLY STAGE"
3700 DATA  "R4", "IF", "HAS SHRUBS >2 M TALL", "HAS >30% LITTER COVER", "THEN"
3710 DATA    "IS LATE STAGE"
3720 DATA  "R5", "IF", "IS GRASS STAGE", "CONTAINS >5% COVER Festuca OR Elymus"
3730 DATA    "THEN", "HAS LESSER GOLDFINCH"
3740 DATA  "R6", "IF", "IS GRASS STAGE", "CONTAINS SNAGS =>3 M TALL", "THEN"
3750 DATA    "HAS WESTERN BLUEBIRDS"
3760 DATA  "R7", "IF", "IS EARLY STAGE", "IS ADJACENT TO MATURE STANDS"
3770 DATA    "CONTAINS LARGE DOWN LOGS", "IS <1 KM FROM OPEN WATER", "THEN"
3780 DATA    "HAS MOUNTAIN QUAIL"
3790 DATA  "R8", "IF", "IS EARLY STAGE", "HAS DENSE, DECIDUOUS BRUSH", "THEN"
3800 DATA    "HAS POTENTIAL FOR WRENS"
3810 DATA  "R9", "IF", "HAS POTENTIAL FOR WRENS", "IS >45% SLOPE", "THEN"
3820 DATA    "HAS WRENTITS"
3830 DATA  "R10", "IF", "HAS POTENTIAL FOR WRENS", "IS <45% SLOPE"
3840 DATA    "HAS DENSE BRUSH", "THEN", "HAS BEWICK'S WRENS", "HAS WRENTITS"
3850 DATA  "R11", "IF", "IS LATE STAGE", "CONTAINS ALDER IN RIPARIAN STRIPS", "THEN"
3860 DATA    "HAS WILSON'S WARBLERS", "HAS MACGILLIVRAY'S WARBLERS (P < 0.01)"
3870 DATA  "R12", "IF", "IS LATE STAGE", "IS ADJACENT TO MATURE STAND"
3880 DATA    "CONTAINS SNAGS >4 M TALL", "THEN", "HAS DUSKY FLYCATCHERS"
3890 DATA  "STOP"
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Figure 23.1. A computer-generated listing of rules used in program BRUSH.

canopy. Inference engines are employed to quickly trim a myriad of possible solutions to only a few, which then are filtered by prompting the user for more specific information. Inference control strategies include evidence-to-hypothesis reasoning (forward-chaining), hypothesis-to-evidence reasoning (backward-chaining), or some combination. Technical reviews of inference control structures may be found in Winston (1977) and Stefik et al. (1983).

Some expert systems represent their control strategy in terms of conditional states or probabilities. Probabilistic control structures vary widely in expert systems. The reason for using uncertainty measures is to increase reliability by combining evidence. A probabilistic approach may prove useful for predicting wildlife responses to habitat conditions by computing probabilities that certain species are present, given that specific habitat conditions have been observed.

The construction of an expert system (Hayes-Roth et al. 1983; Weiss and Kulikowski 1984) begins with a dialogue between the knowledge engineer (a computer programmer) and the human expert. First, the problem is clearly identified. For example, a problem statement may be to diagnose habitat conditions of a particular vegetation type and successional stage in a particular geographic area for the purpose of deducing the presence of species of birds. Second, characteristics of the problem, such as species-habitat interactions, are represented and coded as concepts, facts, and decision rules. Facts may include a classification system of habitats that could assist in predicting species presence. The dialogue becomes critical at this stage, because human experts often apply rules of inference and rules of thumb that are articulated and codified only after careful discussion with the knowledge engineer. Other methods of obtaining expertise may include surveys of a priori professional judgments, such as those gathered by the Delphi technique (Zuboy 1981). The Delphi technique is very powerful and, when properly used, can give a high degree of reliability. At this stage, whether the original problem was defined too vaguely, broadly, or incompletely or whether the problem itself cannot be represented well in this framework will become clear. Usually one then returns to step 1 and refines or redefines the problem. In the third step, the system of rules and facts is tested to verify that they are encoded adequately (Buchanan et al. 1983). Finally, peer review and field validation are used for determining whether the fundamental facts and rules are incomplete or fallacious.

An expert system approach to wildlife-habitat modeling: Two examples

In general, an expert system that predicts wildlife response to habitat conditions should (1) identify species which may occur together under general habitat conditions, such as forest cover types and stages of development; (2) evaluate the response of a species or a set of species to changes in habitat conditions; (3) suggest which habitat attributes would best predict species' patterns of abundance; (4) allow the user to offer information as well as prompt the user for specific information; (5) give a rationale for hypotheses or conclusions reached; (6) be designed to be updated with new facts and rules; and (7) prescribe habitat conditions and recommend methods for creating these conditions to maintain or enhance particular species.

An example of a narrowly defined problem domain for use in wildlife management is predicting bird species' presence in a brushfield habitat following clearcut timber harvesting in the Coast Range of northwestern California. Two demonstration programs, in which I have encoded my own knowl-

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4030 REM
4040 REM   ****** HYPOTHESES FOR DEDUCTIVE INFERENCE ******
4050 REM
4060 DATA  "HAS LESSER GOLDFINCH"
4070 DATA  "HAS WESTERN BLUEBIRDS"
4080 DATA  "HAS WRENTITS"
4090 DATA  "HAS BEWICK'S WRENS"
4100 DATA  "HAS MOUNTAIN QUAIL"
4110 DATA  "HAS WILSON'S WARBLERS"
4120 DATA  "HAS MACGILLIVRAY'S WARBLERS"
4130 DATA  "HAS DUSKY FLYCATCHERS"
4140 DATA  "STOP"
4150 END
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Figure 23.2. A computer-generated listing of contentions regarding presence of eight bird species in brushfield habitats, taken from the demonstration expert system BRUSH written in BASIC.

edge and control rules, will serve to highlight some of the features outlined above.

A rule-based demonstration program BRUSH was written in the BASIC programming language on an IBM Personal Computer and was modeled after the examples in Winston (1977) and Duda and Gaschnig (1981). I supplied data on habitat conditions in brushfields of Douglas-fir (*Pseudotsuga menziesii*) resulting from clearcutting. Through a series of 12 rules of species-habitat relationships (Fig. 23.1), BRUSH deduces the suitability of the site for a variety of bird species. BRUSH's contentions that establish suitability of habitat conditions for eight bird species are presented in Figure 23.2.

A sample run of BRUSH (Fig. 23.3) demonstrates the forward-chaining or data-driven nature of the control structure and the ability of the program to trace and present its own lines of reasoning. A more advanced version of BRUSH may (1) trigger hypotheses from conditional probabilities; (2) incorporate additional rules and hypotheses; (3) allow the user to suggest solutions and to volunteer information; and (4) learn from previous query sessions which rules may be more likely to provide correct deductions under different combinations of responses.

BASIC is a poor language for rule-based deduction systems, although an earlier, full-scale wildlife-habitat retrieval model that used some elements of expert system programming successfully employed BASIC on the Tektronix 4050-series microcomputer (Marcot 1980). BASIC is not designed to manipulate symbols and names extensively, as would be necessary in an expert system. However, the programming language LISP is specifically designed for relating and comparing symbols and is commonly used in expert system programming. I wrote a second example program, GUILD, in LISP (dialect ALISP) on a CDC Cyber 170/720 mainframe computer to demonstrate some advantages of this symbol-based language.

GUILD is based on lists of items and their properties that allow search and retrieval of entities whose properties have user-specified values. For example, the entity "Species-name" is assigned a number of properties, including "Diet," "Foraging-Substrate," and "Habitat." "Habitat" itself is composed of further properties, specifying vegetation types and successional stages. The values of properties are qualitative codes, such as diet items and foraging substrates, or continuous variables, such as mean nest height and home range size.

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RUN
******** PROGRAM 'BRUSH' ********
     DEMONSTRATION EXPERT SYSTEM
        BASED ON RULE-HYPOTHESIS STRUCTURE
        AND FORWARD-CHAINING INFERENCE
This program uses   12   rules to establish one of the
following   8   hypotheses:
  BRUSHFIELD HAS LESSER GOLDFINCH
  BRUSHFIELD HAS WESTERN BLUEBIRDS
  BRUSHFIELD HAS WRENTITS
  BRUSHFIELD HAS BEWICK'S WRENS
  BRUSHFIELD HAS MOUNTAIN QUAIL
  BRUSHFIELD HAS WILSON'S WARBLERS
  BRUSHFIELD HAS MACGILLIVRAY'S WARBLERS
  BRUSHFIELD HAS DUSKY FLYCATCHERS

Respond with YES, NO, or WHY.

Is this true:  BRUSHFIELD HAS <20% WOODY VEGETATION COVER? NO
Is this true:  BRUSHFIELD CONTAINS >5% COVER BULL THISTLE? NO
Is this true:  BRUSHFIELD HAS MOST SHRUBS <2 M TALL? NO
Is this true:  BRUSHFIELD HAS SHRUBS >2 M TALL? YES
Is this true:  BRUSHFIELD HAS >30% LITTER COVER? YES

Rule R4 deduces BRUSHFIELD IS LATE STAGE
Is this true:  BRUSHFIELD CONTAINS ALDER IN RIPARIAN STRIPS? NO
Is this true:  BRUSHFIELD IS ADJACENT TO MATURE STAND? YES
Is this true:  BRUSHFIELD CONTAINS SNAGS > 4 M TALL? WHY
I am trying to use Rule R12
The inference structure has already deduced that:
BRUSHFIELD IS LATE STAGE
BRUSHFIELD IS ADJACENT TO MATURE STAND
IF:
BRUSHFIELD CONTAINS SNAGS >4 M TALL
THEN:
BRUSHFIELD HAS DUSKY FLYCATCHERS

Is this true: BRUSHFIELD CONTAINS SNAGS >4 M TALL? YES
Rule R12 deduces BRUSHFIELD HAS DUSKY FLYCATCHERS
I conclude that BRUSHFIELD HAS DUSKY FLYCATCHERS.
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Figure 23.3. A sample run of BRUSH showing features of forward-chaining deduction. The program progresses through hypotheses by querying the user for pertinent information. The user's responses (underlined) may include "Why," from which the system discloses its reasoning process that led to the asking of a particular question.

A set of LISP functions can then be called to access and manipulate the data base. A brief dialogue with GUILD generated a partial list (Fig. 23.4) of breeding species representing the potential negative impact of a reduction of brush foliage volume in clearcuts 6–10 years old. Field-derived estimates of species densities before and after the brush reduction are given by the program, along with probabilities of species presence (field-derived estimates of percent occurrence of the species in sites having the specified foliage volume levels). Specifying the "mitigate" function triggered the system to output further information, including a set of prescriptions for brush management and species' expected densities resulting from the mitigation activities, estimated from field-derived regressions of species' densities on brush volumes. A more advanced version of GUILD may suggest

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PROGRAM 'GUILD': A LISP-BASED QUERY SYSTEM

? (SETQ BEFORE-STAGE LATE-SHRUB AFTER-STAGE EARLY-SHRUB)
? (TELL-IMPACT)
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	HABITAT STAGE				
	DENSITY (N/40 HA)			PROBABILITY OF OCCURRENCE	
	BEFORE	AFTER		BEFORE	AFTER
SPECIES	LATE-SHRUB	EARLY-SHRUB	PERCENT CHANGE	LATE-SHRUB	EARLY-SHRUB
BLACK-HEADED-GROSBEAK	28.8	5.5	—81	0.95	0.65
CALLIOPE-HUMMINGBIRD	29.8	0.0	—100	0.29	0.00
CHESTNUT-BACKED-CHICKADEE	2.7	2.3	—15	0.38	0.46
FOX-SPARROW	27.3	2.4	—91	0.33	0.31
HERMIT-THRUSH	8.5	2.4	—72	0.57	0.54

DO YOU WANT TO MITIGATE (Y/N)? <u>Y</u>

PRESCRIPTIONS

THE 5 SPECIES IN THIS LIST REPRESENT NEGATIVE IMPACTS ON BREEDING DENSITIES BY A CHANGE IN HABITAT STAGE FROM LATE-SHRUB TO EARLY-SHRUB. THE NEGATIVE IMPACT IS MOSTLY FROM REDUCTION OF SHRUB VOLUME AND COVER. TO MITIGATE THE NEGATIVE IMPACTS ON SPECIES DENSITIES, THE FOLLOWING MANAGEMENT ACTIONS MAY BE TAKEN:

1) RETAIN DECIDUOUS AND EVERGREEN SHRUB COVER ALONG ALL PERMANENT AND EPHEMERAL WATERCOURSES ON THE SITE;

2) RETAIN OR ENCOURAGE POCKETS OF LOCALLY DENSE SHRUB COVER WITHIN THE SITE, AVERAGING AT LEAST 2 M TALL AND 5 M ACROSS; SUCH POCKETS MAY BE SPATIALLY ARRANGED SO AS NOT TO SUBSTANTIALLY INTERFERE WITH REFORESTATION ACTIVITIES;

3) TOTAL SHRUB FOLIAGE VOLUME SHOULD NOT AVERAGE LESS THAN 10,000 CU. M. PER HA.

EXPECTED SPECIES DENSITIES WITH MITIGATION ACTIVITIES

SPECIES	DENSITY WITH MITIGATION PROCEDURES	PERCENT IMPROVEMENT OVER NO MITIGATION
BLACK-HEADED-GROSBEAK	16.5	38
CALLIOPE-HUMMINGBIRD	14.0	47
CHESTNUT-BACKED-CHICKADEE	2.5	7
FOX-SPARROW	14.1	43
HERMIT-THRUSH	5.3	34

SRU 0.310 UNITS.

RUN COMPLETE.

Figure 23.4. A sample run of GUILD showing features of LISP program implementation. User responses are underlined. Note that program response to the "mitigation" option triggered an output of possible habitat prescriptions and expected species' densities.

to the user other habitat features that help predict and influence the species' abundances.

Expert performance

What constitutes expert performance and lends credibility to professional advice? We choose among experts, according to Simon (1977), by "forcing the experts to disclose how they reached their conclusions, what reasoning they employed, [and] what evidence they relied upon." Disclosing the reasoning process lends credibility. Credibility also depends on the expert's actual experience in the field, his or her contribution to the primary literature, and his or her record of validated predictions. Expertise extends beyond familiarity with existing literature and, especially in modeling, involves the ability to distinguish between realistic and unrealistic assumptions.

An explanation facility is an important facet of an expert

Table 23.1 Knowledge-engineering system

System	Problem domain	Inference structure	Features
AGE	General	Forward-, backward-chaining; blackboard[a]	Flexible in knowledge representation and processing
EMYCIN	Deduction, diagnosis	Backward-chaining	Employs certainty factors
EXPERT	Classification	Rules ordered by user	Hypotheses expressed with uncertainty values
HEARSAY–III	General	Blackboard[a]	Supports incremental construction, testing; relational data base
KAS	Deduction, diagnosis	Forward- and backward-chaining	Chooses promising rules via heuristic evaluation function
OPS5	General	User-defined	Flexible in representation schemes
RLL	General	Agenda (flexible) priority system	Library of various control structures
ROSIE	General	Rules ordered by user	English-like syntax

[a]A "blackboard" is a central control medium, used for representing partial solutions and pending program executions.

system because it enables the program to describe its line of reasoning, why it is requesting certain pieces of information, and how it reached a particular conclusion (e.g., Clancey 1983). Such disclosure also helps the system accept new lines of reasoning (new rules or facts) and grow with its use (Winston 1982). A disclosure of reasoning was demonstrated above with BRUSH. The expert system may function better than a human expert because it can easily expose for review its chain of reasoning and inferences, allowing the user to carefully assess its credibility. However, just as with the human expert, output and advice from an expert system should be viewed critically. The system is no better than the data, relations, and reasoning processes it contains.

Quality control of the knowledge base of a wildlife-habitat expert system should include field testing of model predictions and peer review of the adequacy and accuracy of the facts, reasoning process, and controls used in the system. The goal would be to show explicitly, under specified field conditions or ecological contexts, how well or how poorly a system performed. Validation should also include a test of the system's utility, i.e., applicability in an actual management and decision-making environment. Criteria of model validation, which may also be useful for judging "expert" contributions to such a system, were reviewed by Marcot et al. (1983).

Knowledge-engineering systems

Several expert-system-building tools have been constructed that may help reduce development time by an order of magnitude (Table 23.1) (Barstow et al. 1983; see also van Melle 1981). Using such tools allows programmers to compile a knowledge base and to develop inference structures without programming in general-purpose languages such as BASIC, LISP, PROLOG, and FORTRAN. Three of the knowledge-engineering systems—EMYCIN, EXPERT, and KAS—are designed for specific problem domains; the others are general-purpose systems and allow for a greater variety of inference (control) structures, but may sacrifice some ease of use. EMYCIN (van Melle 1979), KAS (Duda et al. 1981), and OPS5 (Forgy 1981) are all well suited to the problem of diagnosing habitat conditions and inferring species' responses. However, knowledge-engineering systems for use on personal computers are coming of age (e.g., Konopasek and Jayaraman 1984).

Questions and cautions

The effort required to produce a full-scale wildlife-habitat expert system is likely to be measured in years of working time (Duda and Shortliffe 1983). Although decision-support systems are becoming increasingly common (Wagner 1982), careful considerations of the cost, need, and utility of such systems seem warranted. Who are the intended users and what are their specific information needs? What specific areas of habitat management could fit into and benefit from an expert system approach? How should a wildlife-habitat expert system be updated and validated? Which human experts should the reasoning processes be modeled after?

Wildlife biologists and resource planners may be the first audience which uses such systems for assessing project impacts and planning alternatives. Other specialists may later integrate their information needs. Predicting the response of wildlife species to habitat conditions and prescribing management activities for mitigation are two functions that can help biologists and planners.

Validation must be an integral part of an expert system. Many ecological problems of habitat management may be ill-suited to the fact- and rule-based structures of expert systems. For example, problems of habitat fragmentation and species' interactions are poorly understood and would be unsound candidates for expert system formalism. Three critical stages in developing a full-scale system are (1) adequately specifying the problem and surveying expert knowledge in a particular problem area; (2) adequately encoding the knowledge into facts and rules of inference and deduction; and (3) validating the system with new field data to determine whether the facts and rules have been represented fully and correctly. Failure to attend to each of these stages would probably result in the building of models in which little confidence could be placed. The expert system should not be used to completely supplant essential field work, such as basic research, population monitoring, wildlife inventory, or reconnaissance for project impact assessment.

The knowledge base must be evaluated for quality, correctness, and completeness. Evaluation also reveals how well an expert system may be expected to perform, given missing or false information. Evaluation by domain experts, such as avian ecologists, would help determine the accuracy of the knowledge base and any advice or conclusions the system provides; evaluation by users, such as habitat managers, would help determine the utility of the system (Gaschnig et al. 1983). Characteristics of expert systems to be evaluated include quality of the system's decisions and advice, correctness of the reasoning techniques used, the nature of the interactions with the human user, the system's efficiency in using facts and rules, and the system's cost-effectiveness. Although no expert system of wildlife-habitat relationships has been formally evaluated, several other types of expert systems have been (Gaschnig et al. 1983).

The relationship between errors in or incompleteness of the knowledge base and errors in the output of an expert system is variable, depending on the level of the rules in the logic structure and the frequency with which the rules are called. In some cases, erroneous or missing rules may accentuate errors in the output. Sensitivity analysis of model output to changes or additions of the knowledge base would help quantify the relationship and thus the need for corrective actions. For example, sensitivity analysis of the MYCIN program revealed that the certainty factors used in the program to weight different responses influenced the output less that did the semantic and structural context of the rules per se (Gaschnig et al. 1983).

Error rates of fully evaluated systems, such as MYCIN, R1, or PROSPECTOR, are generally low as long as the systems are used within appropriate problem domains. Such evaluations may serve to show the usefulness and evolutionary development of a wildlife-habitat expert system (e.g., see Buchanan and Shortliffe 1983). Our current knowledge of wildlife-habitat relationships requires much additional development and testing, and a wildlife-habitat expert system cannot be expected to perform any better than our own knowledge allows. The greatest benefit of such an expert system, however, would be in distributing existing expertise in narrowly defined problem domains (such as response of songbirds to clearcutting Douglas-fir forest) to users that require but lack such expertise.

It is my opinion that an expert systems approach that incorporates field-monitoring information, discloses its reasoning process, and helps prescribe habitat conditions to suit particular species may be a valuable tool for habitat managers and decision makers, if adequately validated and applied to appropriate problem domains. However, risks of applying untested systems may be high if pertinent facts and reasoning processes are developed in isolation from extensive peer review and field validation.

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