AI Methods in Support of Forest Science: Modeling Endemic Level Mountain Pine Beetle Population Dynamics

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Abstract. Expert systems are an excellent way to organize existing knowledge for use by land managers or research scientists. Our objective was to develop an expert system that would deal with endemic (low) levels of mountain pine beetle in the lodgepole pine type of the Intermountain West. Initially, we wrote a knowledge acquisition program to help obtain information on the functioning of the system from five expert forest entomologists. This information was then fed into an expert system generator to produce the expert system. Users provide parameters (e.g., average diameter at breast height of both the stand and infested trees, stand elevation, and various temperature values) pertinent to the stand in question. The expert system uses this information to determine if the mountain pine beetle population will increase, decrease, or remain static for the coming year. Users of the system say it mimics the current knowledge closely and gives useful results. Following model verification, we will provide it as a tool for use by resource managers. We anticipate that the primary use for expert systems of this type will be to identify areas where further research is required.

Lodgepole pine (*Pinus contorta* Dougl. var. *latifolia* Engelm.) forests cover 13 million acres in the western United States (Wellner 1975) and approximately 50 million acres in western Canada (McDougal 1975). Most of these acres are susceptible to attack by mountain pine beetle (*Dendroctonus ponderosae* Hopkins [Coleoptera: Scolytidae]), which is one of the main killers of lodgepole pine. During full-blown mountain pine beetle epidemics, millions of lodgepole pine are killed annually in the western United States and western Canada (Amman et al. 1988).

The USDA Forest Service Mountain Pine Beetle Project[1] initiated a research agreement with the Department of Forest Resources at Utah

[1] Gene Amman, Project Leader, USDA Forest Service, Intermountain Research Station, Ogden, Utah 84401

State University, Logan, Utah, to evaluate potential applications of artificial intelligence (AI) in their research program. During the past 20 years, researchers on this project have developed an extensive knowledge base about the epidemic (catastrophic or outbreak) phase of mountain pine beetle infestations in lodgepole pine forests. This information has provided a better understanding of the dynamics of mountain pine beetle at outbreak levels (Amman and Cole 1983, Cole and Amman 1980, Cole et al. 1985).

Direct control of mountain pine beetle during outbreak is usually only minimally successful, and more attention should be placed on silvicultural means of suppressing mountain pine beetle populations before an outbreak occurs. Better understanding of the dynamics of low or endemic level (prior to outbreak) mountain pine beetle populations should ultimately lead to the development of preventive strategies.

Years of working with epidemic mountain pine beetle populations have improved knowledge of endemic situations. Various biological interactions (e.g., diseases and mountain pine beetle populations) are being evaluated to ascertain their relationship with endemic mountain pine beetle populations. Research and existing knowledge will form the basis for developing useful expert systems.

The focus on endemic population levels represents a new and largely unexplored aspect of research into mountain pine beetle population dynamics. Researchers have extrapolated from findings based on years of studies of epidemic outbreaks of mountain pine beetle in lodgepole pine. Their extrapolations were based on professional judgments accumulated during years of informal, unstructured observation. Little empirical information is available to help researchers develop models to guide research on the population dynamics of this pest.

We sought to capture the largely intuitive knowledge of these researchers and to organize it into a research expert system with communication and feedback capabilities. This dialogue between the expert system developer and the expert is the prime means of extracting information. Feedback makes it possible to explore aspects that experts had not previously considered. This paper discusses perspectives that influenced design of the investigation, the procedures used to develop the system, our findings, and recommendations for further work.

Nature and Focus of the Investigation

This exploratory study details the development of an expert system that was designed primarily as a research tool. This expert system will be scrutinized by other experts, refined, and further evaluated for applicability to specific management situations. The investigation involved five forest entomologists from both Forest Service Research and State and Private Forestry. The foresters who were selected work in the western United States and are considered mountain pine beetle experts by their peers.

Mountain pine beetles have a dramatic impact on lodgepole pine forests in the West, and a better understanding of the interactions between the beetle and the tree in low-level infestations is critical to minimize loss. An expert system would be one way to integrate and utilize existing knowledge. To explore this possibility, we 1) extracted and represented the experts' knowledge about endemic population dynamics of mountain pine beetle and determined how this knowledge guides their work, 2) let the experts review this information (via summary computer outputs) for clarification and refinement, and 3) developed an expert system that reflected their conceptual models of the knowledge domain. This system incorporated the steps that the expert needed to arrive at a logical conclusion.

We are now evaluating how expert systems can be used to stimulate and focus dialogue among researchers concerning low levels of mountain pine beetle in lodgepole pine forests. Ultimately, these programs will be used to identify high-risk forest stands that could be treated to prevent catastrophic losses. The programs will be evaluated by comparing results with the findings from field studies in lodgepole pine forests of the western U.S. We

anticipate that the primary use for expert systems of this type will be to identify areas where further research is required.

Research Expert Systems: Expert Systems in a Research Context

We altered traditional development methods and concepts associated with expert systems to facilitate working in a research environment. Our approach violates some commonly accepted criteria and assumptions about the types of problems suitable for expert system development. As a result, we call our programming product a "research expert system." The research expert system borrows heavily from expert system methodology, but differs in assumptions about the function of the system, the "expert," and the nature of the knowledge base. These differences are summarized in Table 1.

Methods

Our goal was to develop AI methods and concepts that facilitate communication among researchers by incorporating, into an expert system, knowledge that would otherwise not be available to the scientific community. Such a system could provide feedback to the system's users (individual researchers, teams of researchers, and managers). Feedback would *clarify important elements (e.g., objective statement, informational flow, and model diagram) of the process* so users could better identify patterns, regulari-

Table 1. *Differences in assumptions and requirements associated with expert systems and research expert systems.*

EXPERT SYSTEM[a]	RESEARCH EXPERT SYSTEM[b]
Task or Function of the System	
Experts are viewed as problem solvers who solve problems more quickly than nonexperts. A timely solution has high value.	Researchers are much less concerned with solving specific problems but seek to increase knowledge of a topic, thereby enhancing future problem-solving capability. Ideally, the research expert system system will help distinguish known factors and relationships from those which are not yet fully understood. The time required to produce definitive results is unpredictable.
Nature of Expertise	
The knowledge engineer packages the expertise of acknowledged experts for use by nonexperts.	A researcher seeks to expand knowledge of the domain. The knowledge engineer captures and packages the researcher's conceptual model to facilitate scientific dialogue and testing.
Nature of the Knowledge Base	
The knowledge base is stable and need not be substantially modified for a long period.	Knowledge evolves and reflects new findings. Prototypes must rapidly reflect new findings and be formally evaluated.

[a] Widman et al. (1989).
[b] Bartos and Downing (1989).

ties, or inconsistencies within the designed system, and recognize opportunities for additional research.

It seemed that feedback of several types would be useful at a number of stages during model development and testing:

Researchers' initial perceptions of the model.
When researchers are asked to comment on the accuracy of the model and the factors which it incorporates.
When researchers from other disciplines provide additional information about the model.
When colleagues review the model.
When alternative models are incorporated or tested.
When researchers and managers attempt to coordinate the collection of data.

The Researchers and the Nature of Their Knowledge Domain

Initial interviews, observation, and conceptual diagramming. We briefly described the purpose of the model to each of the five researchers and pest management specialists that were interviewed. As noted above, the model was being developed to better understand the dynamics of endemic populations of mountain pine beetle in lodgepole pine forests in the western United States. These experts were then asked to formulate a more specific objective than that which we described. For example, we said the model was being developed "to predict the number of new lodgepole pine tree kills per stand next season" or "to predict the change in mountain pine beetle population numbers per stand next season." We asked the researchers to categorize the nature of this change: for example, "double or more," "little or no change," "significant decline," "beyond our understanding—unable to predict." Researchers were then asked to specify the kinds of information (factors and subcategories) that they would need to make these predictions (Fig. 1a).

Researchers were also asked to name the variables that they thought would be associated with particular factors. For example, we were told that winter and spring temperature patterns are required to estimate overwintering brood survival. We then asked researchers to identify other factors that would be associated with estimates of the overwintering brood survival. This process of identifying factors and relationships that might be associated with a particular objective (e.g., estimating overwintering brood survival) is illustrated in Figure 1a.

We incorporated our main expert's suggestions and then had him review and modify the model. Figure 1-B2 illustrates the completed diagram that he developed concerning overwintering brood survival. The diagram illustrates one stage of feedback that we used to elicit responses. This and similar models often required several iterations before the researcher thought it adequately represented his views. Providing an opportunity to review models let him correct discrepancies and omissions and occasionally prompted him to restate the initial objective.

The diagrams that we provided for researchers to review helped them focus on endemic rather than epidemic populations, although the shift in emphasis did not always occur smoothly. Several researchers were initially reluctant to speculate about endemic population behavior. We often had to remind them that the model concerned endemic populations.

In addition to the diagrams generated during the interviews, we provided other types of graphics (Fig. 2) for researchers to review during the process of model development. Finally, we also spent a limited time in the field with several of the investigators; this allowed us to probe for additional information—why they looked in certain locations or how certain stand conditions might affect mountain pine beetle behavior, for example.

Predictions, Certainty Factors and Qualifying Comments for Factor Combinations

When a conceptual model had been diagrammed successfully (when the expert offers no additional changes), a printout (Fig. 3) of all combinations of factors and subcategories was generated using a program written for this purpose.[2] Each expert was

[2] KAP (Knowledge Acquisition Program). Designed and programmed by Kent Downing, January 1990.

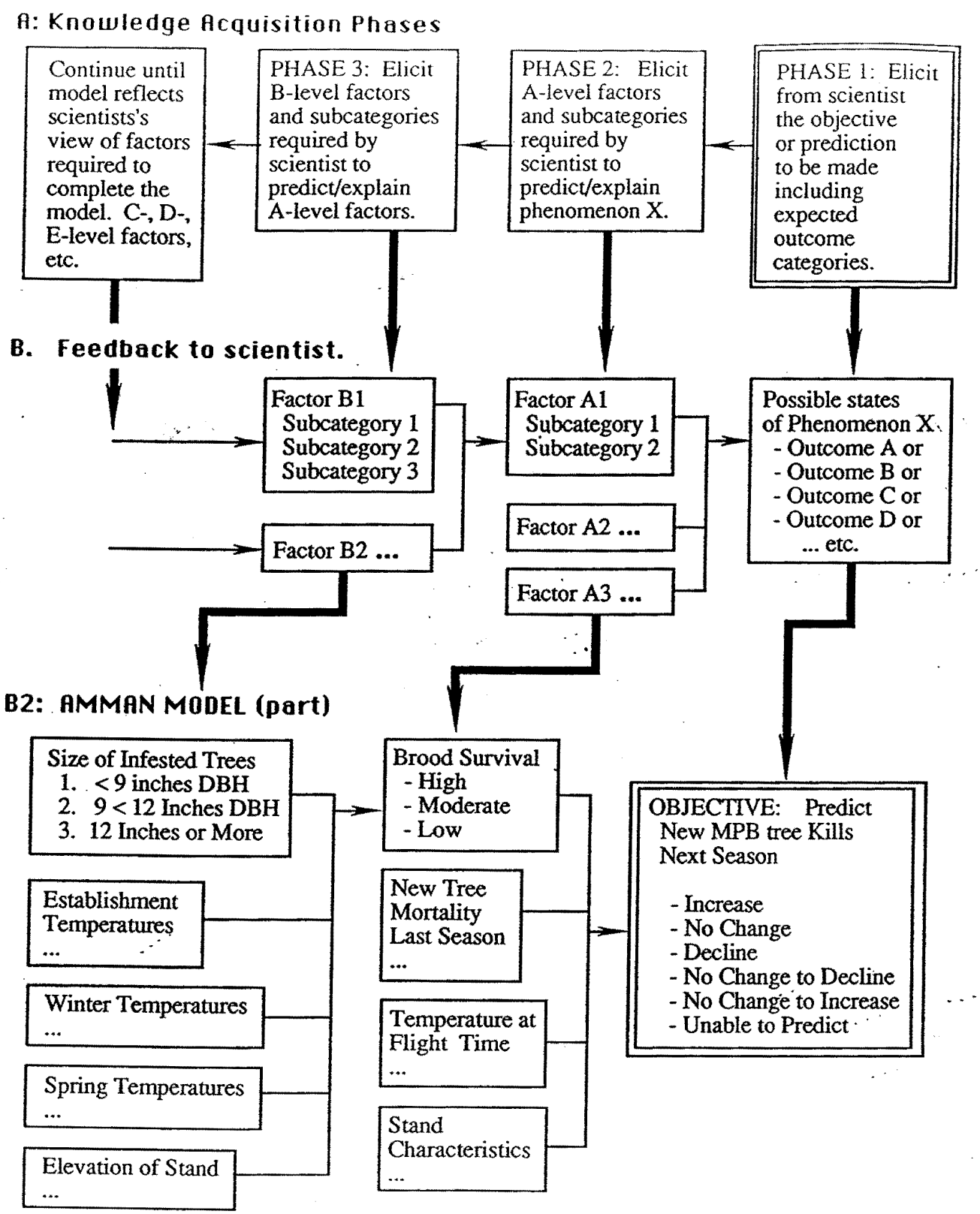

Figure 1. *(A) Knowledge acquisition phases including factors and subcategories, (B) feedback to experts including the structure of the acquired knowledge base—factors and subcategories, (B2) completed diagram developed by one expert concerning overwintering brood survival.*

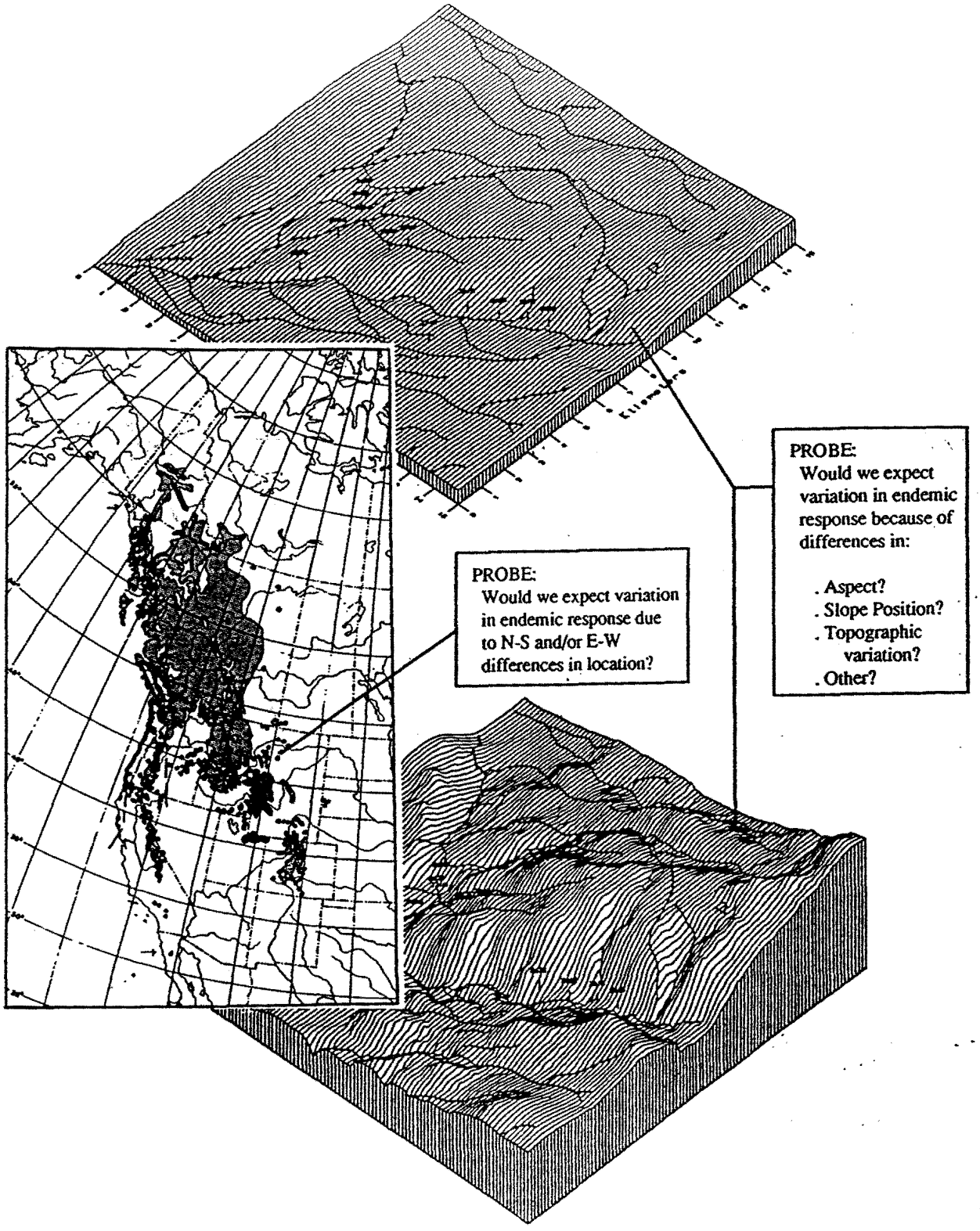

Figure 2. *Graphics used to trigger the expert's thought processes. The three-dimensional graphs are of a study site on the Medicine Bow National Forest in southeastern Wyoming. The map shows the distribution of lodgepole pine throughout North America.*

OBJECTIVE: To predict/explain fall/winter/spring brood survival.

TOTAL RULES ENTERED: 108 RULE NUMBER : 4
PREDICTION: low
Estimated certainty value [0-10 with 0 = none.]: 10

Case Conditions

establishment_period_temperatures	October average or higher
winter_temperatures	one week minus 35 degrees F.
spring_temperatures	No cold snap
elevation_of_stand	< 9 inches DBH

COMMENT 1:
Beetles have 3 things going against them: winter temps, elevation, and size of infested trees, but minus 35 degrees F is by far most significant.

Predictions, certainty values, and comments entered here.

OBJECTIVE: To predict/explain fall/winter/spring brood survival.

TOTAL RULES ENTERED: 108 RULE NUMBER : 5
PREDICTION: low
Estimated certainty value [0-10 with 0 = none.]: 8

Case Conditions

establishment_period_temperatures	October average or higher
winter_temperatures	one week minus 35 degrees F.
spring_temperatures	No cold snap
elevation_of_stand	9 < 12 inches DBH

COMMENT 1:
Protection from - 35F by deep snow coupled with large tree diameters could result in fair beetle production, but would no more than maintain status quo.

Figure 3. *Example of the output produced from the knowledge acquisition program of all combinations of factors and subcategories.*

then asked to evaluate all combinations of interactions and to record his evaluations directly on the printout. A printout was developed for each expert's situation, and he was allowed a reasonable time period to complete the request. The experts were asked to enter three types of information for each combination:

1) A prediction for the various case conditions as to what the brood survival will be the following year (low, medium, or high).
2) A numerical value (1 to 10 where 0=none) that represents the researcher's subjective estimate of certainty in the prediction.
3) One or more comments that qualify or otherwise explain the rationale for the prediction. Published reference citations and other sources that support or refute the prediction could be entered.

This phase of the process may generate a considerable number of combinations of factors and subcategories, each requiring input by the expert as to a prediction, certainty factor, and supporting information. Each combination is a distinct case situation. In the example concerning the prediction of fall/winter brood survival, researchers could provide input on five factors, three of which had three subcategories and two of which had two subcategories. Thus, this portion of the model could involve a total of 108 combinations—all possible combinations of factors and subcategories.

The researcher was asked to predict the outcome of each combination of factors and subcategories. The result is to capture subtle interactions within each combination and to show how a change in one or more variables (e.g., winter temperature, elevation of stand, Fig. 3) would affect other variables. By this process, interactions are reflected in the rules produced by the following rule-induction procedures.

Rule Induction and Generation of the Research Expert System

The factor combinations and predictions were processed by a rule induction program.[3] The rules generated were a subset of the initial set of factor combinations. For example, 62 rules were generated from the initial 108 factor combinations concerning brood survival when certainty factors (supplied by the experts) were included, and to 18 when they were excluded. Certainty factors are one way to store, generate, and reason with uncertain imprecise knowledge (Rothman 1989).

This version of the model that included logical rules with associated predictions was presented in three alternative formats for the researchers to examine for errors and inconsistencies. Formats included 1) printouts of decision trees (Fig. 4), 2) printed lists of rules (Fig. 5), and 3) screen displays during and at the end of run-time program consultations (Fig. 6).

Data, Predictions, and Verification

Field data are processed through the research expert system to generate expected outcomes or predictions. An example would be:

Stand identification code? = frcr-lp10-023245
What is the Mean Diameter of the Stand? = <8"
What was the Pattern of Winter Temperature last Season? = One week or more of minus 35°F
Prediction of new lodgepole pine tree kills next season is DECLINE compared with last season.

This makes it possible to compare results generated with the model with actual events observed under field conditions, a key step in model validation.

Results and Discussion

The process of model development clarified areas of disagreement among researchers about the priorities and objectives of investigation, the nature of factors and subcategories required for prediction, the hypothesized relationships, predicted outcomes, and levels of certainty. These differences surfaced when each expert reviewed the model he had formulated and when each researcher examined the diagrams

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Classification tree for BROOD SURVIVAL.

What is the value for winter_temperatures?
  one week minus 35 degrees F :: Prediction = low BROOD SURVIVAL
  no week of minus 35 degrees F
    What is the value for size_of_infested_trees?
      < 9 inches DBH :: Prediction = low BROOD SURVIVAL
      9 < 12 inches DBH
        What is the value for establishment_period_temperatures?
          October much below :: Prediction = low BROOD SURVIVAL
          October slightly less
            What is the value for elevation_of_stand?
              lower third :: Prediction = moderate BROOD SURVIVAL
              middle third :: Prediction = low BROOD SURVIVAL
              upper third :: Prediction = low BROOD SURVIVAL
          October average or higher
            What is the value for elevation_of_stand?
              lower third :: Prediction = moderate BROOD SURVIVAL
```

Figure 4. *Example printout of a decision tree produced by KnowledgeMaker.*

```
Rule Induction for BROOD SURVIVAL

Rule 1
  If winter_temperatures is one week minus 35 degrees F
  then BROOD_SURVIVAL is low.

Rule 2
  If winter_temperatures is no week of minus 35 degrees F
  and mean_diameter_infested_trees is < 9 inches DBH
  then BROOD_SURVIVAL is low.

Rule 3
  If winter_temperatures is no week of minus 35 degrees F
  and mean_diameter_infested_trees is 9 < 12 inches DBH
  and establishment_period_temperatures is October much below
  then BROOD_SURVIVAL is low.

Rule 4
  If winter_temperatures is no week of minus 35 degrees F
  and mean_diameter_infested_trees is 9 < 12 inches DBH
  and establishment_period_temperatures is October slightly less
  and elevation_of_stand is lower third
  then BROOD_SURVIVAL is moderate.
```

Figure 5. *Example printout of a list of rules produced by KnowledgeMaker.*

```
RESULTS OF ANALYSIS     Stand Identification Code: frcr-lp12-043551
DATE:  6 19 1990        TIME:  14 55 23
  mean_stand_diameter,                    8 inches DBH or more
    = STAND_STRUCTURE                     SUPPORTS BUILDUP
  winter_temperatures,                    no week of minus 35 degrees F
  mean_diameter_infested_trees,           12 inches DBH or more
  establishment_period_temperatures,      October temperatures average or higher
  elevation_of_stand                      within LOWER THIRD of elevation range
    = BROOD_SURVIVAL                      HIGH
  new _tree_mortality_last_season,        one clump of 4-7 trees in stand

PREDICTED NEW TREE KILLS
COMPARED WITH LAST SEASON                 INCREASE.
```

Figure 6. *Example screen display at the conclusion of a run-time program consultation.*

and programs that represented perspectives of his colleagues.

The detail required for models varied with the purpose of the model. Management-oriented models emphasized changes in long-term factors; scientific models were more likely to include fundamental short-term and long-term properties. These differences must be resolved when field data are collected for model validation. We are now attempting to determine if the research expert system models will help users understand why it is necessary to collect certain types of new information.

Providing feedback in different formats (e.g., diagrams, predictions, research expert system prototypes, and explanatory information) facilitated identification of conceptual problems. The model can be modified accordingly. Feedback was important at all stages of the process.

Simplifying and automating the model-building process facilitated interaction between knowledge engineers and experts. Initial diagramming, an iterative process and joint effort, required approximately one to two days. The researcher required several more days to enter predictions, certainty factors, and qualifying comments. It often required no more than two to four hours to create the first operational research expert system. Adding explanations of the outcomes often entailed several additional days of collaboration between a researcher and the knowledge engineers. The need to modify or refine information was occasionally apparent at any stage of the process.

Including knowledge from several experts allowed us to integrate diverse but complementary perspectives into one model. It was not necessary, however, to achieve consensus, but rather to formulate competing models for field testing.

Research expert system development facilitated and focused interdisciplinary communication. Individual researchers often suggested that we obtain advice of specialists in other fields. For example, one entomologist proposed asking silviculturists to refine the representation of a critical silvicultural factor.

Several researchers thought that research expert system development may facilitate efforts by researchers and managers to integrate data collection. In addition, developing clearly defined and comprehensible models gives credibility to requests for collecting specific kinds of data.

Knowledge acquisition is a complex and time-consuming process. Several experts expressed the view that their ideas could not easily be captured via this process. Some were reluctant to "give away" the valuable knowledge acquired through years of work and observation to a research expert system unless their contributions were appropriately acknowledged.

Evaluating the Contributions of AI to Forest Science

We sought to improve our ability to develop, implement, evaluate, and modify expert systems in forest science. Our methods addressed the inability of experts to describe their own reasoning processes (Shapiro 1987). Our investigation attempted to capture and organize the incomplete and ill-defined mental models of "reality" that researchers develop, models that have not yet been suitably refined for systematic scientific examination.

Researchers frequently made important modifications to facts and relationships when they reviewed models. We developed a general procedure to rapidly revise (re-prototype) models to reflect changes made by them.

We did not attempt to compare the efficacy of AI methods to other methods that researchers use to conceptualize and clarify information. Perhaps the outcome would have been similar had these AI-based procedures not been employed. We cannot yet unequivocally state that our methods enable research to progress more efficiently. Additional research is required to determine the benefits of AI methods in forest science and the conditions under which these benefits can be realized.

"For centuries, the physical sciences have improved our understanding of the natural world through observation and experimentation. ... there is no compelling reason to believe

that the same methods will not work [with AI] as well" (Buchanan 1988, page 209).

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Dale L. Bartos is an operations research analyst with the Intermountain Research Station. Prior to assuming his current position in 1984, he was with the station for 12 years as a range scientist on the aspen ecosystem project. Bartos holds B.S. and M.S. degrees from Fort Hays Kansas State University, and a Ph.D. degree in range science from Colorado State University. His principal research interests are in systems modeling and ecological processes.