The SBR approach enjoys the potential advantage of global coverage and multipurpose capability. Surveillance protection can be extended to force concentrations anywhere, such as naval battle groups, and to the territories of allied nations; it can prove valuable in a world periodically convulsed by outbursts of regional conflict. Tracking of aircraft can in many cases be initiated as soon as they leave their operating bases, thereby providing a measure of identification and mission purpose. The system could also be used for assisting international air traffic control and search-and-rescue operations. On the negative side are two often-cited drawbacks, vulnerability to attack and high cost. These are valid concerns that apply to many space-based applications of military technology.

Currently SBR is in a phase of concept definition and technology development. The Department of Defense is interested in bringing together the various mission requirements to see if the system can be justified. A decision to deploy an operational system will probably depend as much on budgetary considerations as on perceived usefulness, which is generally held to be considerable. The required advances in technology appear to be reasonable, and the development of a baseline system could proceed at this time. A precursor system with the capability to demonstrate the usefulness of the concept to prospective users could consist of one radar sensor at a reasonable altitude. This satellite could be hardened at least against natural background radiation effects and could incorporate some level of resistance to electronic countermeasures. Properly instrumented, this system would also function as an invaluable test-bed, yielding results that could reduce significantly the technical risk inherent in the deployment of an operational system.

One could conceive of a future system architecture that uses a versatile space-based instrument to perform object discrimination tasks (as in SDI) in addition to carrying out wide-area surveillance missions (as in ADI). Although the possibility of such synergism is appealing, effective surveillance and high-quality discrimination with a common sensor have traditionally been deemed incompatible. It would be an impressive achievement in radar technology to demonstrate a unified sensor concept that accommodates both missions without compromising the required levels of performance.

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Artificial Intelligence and Natural Resource Management

ROBERT N. COULSON, L. JOSEPH FOLSE, DOUGLAS K. LOH

The use of artificial intelligence (AI) in natural resource management began with the development of expert systems for problem-solving and decision-making. The use of expert systems in turn led to the development of other AI procedures pertinent to natural resource management. Of particular significance are (i) integrated expert systems, which link management models with natural resource models; (ii) intelligent geographic information systems, which permit interpretation of relations within and among landscape data themes; and (iii) AI modeling of animal behavior and interaction with the environment. These procedures provide new ways to view classic problems in systems analysis.

RESEARCH IN ARTIFICIAL INTELLIGENCE (AI) HAS BEEN performed mainly in computer science and cognitive psychology. The issues have been straightforward: (i) definition and classification of principles of intelligent behavior; (ii) design and development of computer systems (hardware and software) capable of mimicking intelligent behavior; and (iii) use of such systems to solve problems of perception, analysis, and adaptation. The recent availability of dedicated AI workstations and knowledge-systems software has hastened the introduction of AI techniques and products into other sciences. In the literature on AI, which has been developed principally for potential practitioners of

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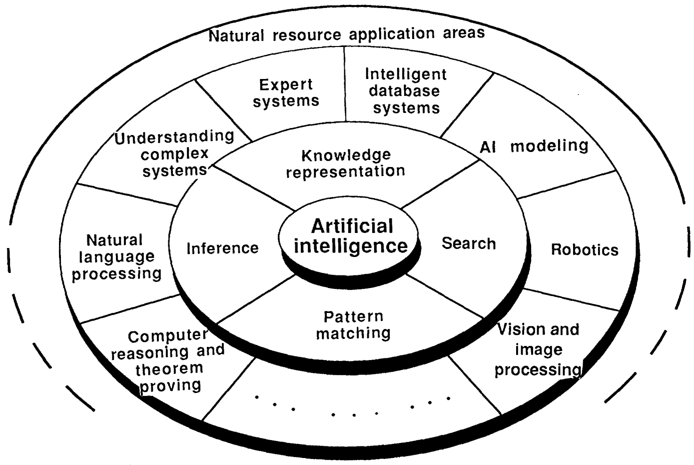

Fig. 1. Scope of application areas for AI as applied to NRM.

the technology, broad categories of applications (such as expert systems, robotics, vision and image processing, and natural language processing) are explained, basic methodologies (knowledge representation, inference, pattern matching, and search procedures) are discussed, and specific applications in various academic specialties (such as business, medicine, geology, and agriculture) are described (Fig. 1) (*1–3*). This literature has introduced the subject to many potential users of the technology, although it has also created a perception that AI applications are simply an array of new extension tools for natural resource management (NRM) (*4–6*).

Applications of AI in NRM (*7*) resulted from interest in expert systems. The availability of developmental software and symbolic languages for microcomputers hastened introduction of the technology. Diagnostic and decision-aid expert systems are useful for problems that have discrete boundaries or are symbolic in nature, and for which human expertise is scarce or expensive (*5, 6*). However, the application of expert system techniques in NRM has not been a simple task and has been complicated by the existence of multiple experts, the inherent uncertainty characteristic of biological and economic data, large and complex databases, and a knowledge domain that is tied to a changing landscape. These factors have required a more detailed examination of basic principles and techniques associated with the parent discipline, AI, and have led to new tools and methodologies for addressing issues in NRM and landscape ecology. Our objectives are to identify and describe AI applications directed to (i) development of integrated expert systems for problem-solving and decision-making, (ii) development of intelligent geographic information systems for landscape management, and (iii) modeling animal populations and environmental interactions.

Integrated Expert Systems for Problem-Solving and Decision-Making

Resource managers must be aware of the ecological, economic, and social consequences of their actions if they are to make informed decisions. Managers must comprehend information that spans several disciplines and ranges from basic social values to highly technical research results. Since the late 1960s scientists have used systems analysis and simulation modeling to abstract the important features of complex systems (*8*). More emphasis has been placed on gathering information than on effective and efficient use of available information for decision-making and problem-solving. Although conventional decision aids (*6*) and microcomputers have expedited the practical application of some of the knowledge available, the problem-solving and decision-making routine of resource managers remains essentially unchanged. However, when fundamental concepts from systems science are combined with principles from AI, especially with regard to expert systems, issues of NRM can be approached from new perspectives.

Expert systems in NRM: Uses and limitations. Of the various computer-decision aids for NRM that can use simulation models, expert systems have been chosen for their usefulness and potential impact (*4–6*). Expert systems applications have successfully captured and focused human expertise on complex problems in several domains (*9*) and in many cases have achieved a level of performance that equals or exceeds that of recognized human experts. In NRM, however, applications have been relatively few and recent.

Two types of expert system applications have been developed for NRM: diagnostic systems and simulation delivery systems. In diagnostic systems the knowledge base is bounded and includes a discrete set of alternatives for problem-solving and decision-making. Examples include systems for identifying species (*10*), for giving financial advice (*11*), and for selecting pest control options (*12*). Simulation delivery systems are concerned with the useful manipulation of simulation models. The execution of the model is controlled by an attached expert system that manages inputs to the model to ensure that they are correct and sufficient. The expert system component also interprets output from the model within the bounds of intended use. COMAX (*13*) is an example of a simulation delivery system that provides an expert system interface to a cotton model. The system helps growers schedule irrigation, fertilizer application, and harvest by searching for a defoliation date, water, and nitrogen conditions that improve simulated yields within agronomic constraints.

The use of expert systems in NRM has two limitations. First, rules, which are the primary way of representing knowledge in virtually all expert systems, are not well suited to providing advice in problems that involve natural systems. Second, management itself is a broad-based problem. Both limitations reflect the requirement in development of expert systems that the problem be well defined (*14*). If the limits are not explicitly stated and the system is not constrained to give advice only within appropriate limits, then erroneous advice can be given without warning to the user.

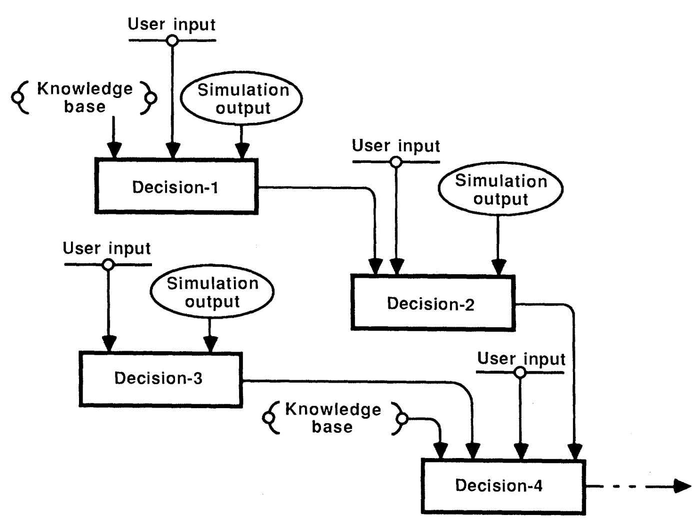

Fig. 2. The breakdown of management into a system of decisions linked by information flow. Information exists in four main forms: (i) user input of objective data, (ii) knowledge stored in the knowledge base, (iii) simulation output (used to update the knowledge base), and (iv) previous decisions or choices made that reflect the opinion of experts. [Adapted from (*12*), courtesy of the National Cotton Council of America]

The distinction between models of surface knowledge, which describe associations and correlations, and models of deep knowledge, which describe causative relation, is central to the first limitation. Natural systems are dynamic and not completely understood. Thus scientists seek to explain natural phenomena in terms of causation and not correlation. Furthermore, scientific research on natural systems is evaluated by the extent to which models of the underlying laws of nature can be hypothesized, tested, or elucidated. Rules are extremely good at describing associations, such as if boll weevil infestations are observed in early-squaring cotton and boll weevils are not controlled, then serious yield losses will occur. By contrast, rules are not well suited to describing deeper, causative knowledge. For example, cotton yield losses due to boll weevil infestation are dependent on weather, rates of development of the weevil larvae, plant growth and development, temperatures in the field at the soil surface, humidity, and several other factors. Writing rules to describe such relations would be tedious and inexact. Mathematical models and other representation schemes such as semantic nets are better suited to describing such deep knowledge.

The second limitation is one of scope. Expert system applications are most successful in narrowly defined problem domains, yet NRM is an open-ended problem. Optimal use of farmland, for example, involves agronomic, pest management, and economic decisions that are interrelated. A proper computer-decision aid should consider the complexities involved in these interrelations. Isolated solutions have limited usefulness.

Integrated expert systems in NRM. Integrated expert systems (IEXS) were developed to overcome these two critical limitations in applying expert systems to agricultural problems (*15*). Two strategies stressed in IEXS are described below: separation of deep knowledge of theory associated with scientific and economic systems from surface rules for managing those systems; and the application of systems analysis approaches to the management activity (*12*).

Building systems that provide an understanding of a problem domain that is separate from knowledge about how to solve problems is one of the main goals of all knowledge-based systems (*2*). In expert systems this separation is evident in the distinction between the knowledge base and the inference engine, that is, the rule interpreter. In practice, however, rule-based expert systems rely on rules both for the representation of relations in the problem domain and for the problem-solving logic. The inference schemes used are too general and too shallow to provide much more than search and conflict-resolution strategies.

The desired separation, then, is possible only through the use of other knowledge representation schemes apart from or in addition to rules. The major tools for building knowledge-based systems (for example, KEE, ART, and Knowledge Craft) all allow for a specific representation of domain knowledge apart from and in addition to rules that reference that knowledge. In such systems, rules can act separately from the knowledge base to describe how to solve problems within the subject domain. In this context rules are an appropriate way to encode problem-solving heuristics within the constraints of a natural system.

In IEXS, classical systems analysis is applied to the problem of management. The system is a decision system; the modeling methodology used is rule-based expert system constructs; the components of a management system are the specific decision points and choices that need to be made (Fig. 2). The linkages between these components are information from one of three sources: the user, the knowledge base, or previous decisions and choices that have been made. A decision network is created in which each node of the decision system is modeled by a rule-base module and the catalog of decision nodes represents the range of problems to which the system can respond. Once the user has identified a starting point within the decision network, the system produces a chain of decisions by moving through the modular rule bases to reach a conclusion. In this way the system provides advice on a wide array of management problems while keeping each modular rule base well focused and defined.

Systems that contain these two elements to some degree, that is, a natural system model and a management system model, include the COMAX system (*13*), the POMME system for pest management in apple orchards (*16*), the CALEX system for cotton management in California (*17*), and the COTFLEX system for farm management in Texas (*15*). In COTFLEX, a frame-based representation of a Texas farm in the Southern Blacklands is augmented and updated by simulation models of (i) plant and pest development and interaction and (ii) economics models for price forecasting and farm financial analysis based on current farm policy. This deep-knowledge description of the natural and economic systems forms the basis for the rule-based management model that provides users with advice (Fig. 3). Thus a field has certain attributes, such as soil type, size, crop and pest histories, and crop planted, which are inherited by its subclasses, the individual fields. All cotton fields also have attributes, such as planting date, soil type, pest abundance, and phenological stage of the crop. When simulation models are available, future values and trends of pest abundance, market prices, and net farm income can be added to the system.

Conventional and Intelligent Geographic Information Systems

Landscape ecology, which is the study of structure, function, and change in heterogeneous land area composed of interacting ecosystems (*18*), deals with the level of ecological organization that service agencies in federal and stage government (such as the Forest Service, the Park Service, the Fish and Wildlife Service, and state forestry agencies) are charged to manage. Farm and ranch managers are also concerned with this level of organization. Landscape ecology, an emerging discipline within ecology, is a response to the need to understand (i) development and dynamics of pattern in ecological phenomena, (ii) the role of disturbance in ecosystems, (iii) characteristic spatial and temporal scales of ecological events, and (iv) interactions among multiple ecosystems (landscape elements) (*19*). One of the principal technologies available for studying landscape ecology and landscape management is the geographic information system (GIS). The usefulness of the conventional GIS can be dramatically enhanced by incorporation of AI in its design.

Conventional GISs. A GIS is a computerized mapping system for capture, storage, retrieval, and analysis of spatial and descriptive data. In a GIS, coordinates that represent a base map of a geographical area can be digitized, manipulated, and reproduced on a computer screen. Landscape features (or "data themes") (for example, vegetation types, soil types, lakes, river drainages, and road systems) can be overlaid on the map (Fig. 4). Spatial relations among the various data themes can be examined and specialized maps developed. Different map scales can be adjusted or coordinated in a GIS; high-resolution graphics terminals permit representation in extraordinary detail. For organizations involved in landscape management, GISs are useful in assessing consequences of land management practices, taking inventory of natural resources, defining land-use patterns, delineating animal habitat, and applying to other activities.

Existing GIS technology has been developed by using conventional computer science techniques. All GISs contain four components: (i) a data input subsystem that collects and processes spatial and descriptive data derived from maps, remote sensors, and other sources; (ii) a data storage and retrieval subsystem (that is, a database management system); (iii) a data manipulation and analysis subsystem that consists of evaluation functions, simulation models, and so forth; and (iv) a data-reporting subsystem for display of portions of the original database as well as manipulated data (*20*). Relations among elements of the landscape are undefined. However, knowledge of the interrelations is often quite advanced. For example, harvesting a stand of trees in a forest is known to influence subsequent vegetation dynamics, animal habitat, water quality in streams, fish populations, and other aspects of the landscape. The knowledge that relates to these subject domains consists of technical information, simulation models, evaluation functions, and expert opinion. The knowledge base for a given geographic area is often quite large and is rarely, if ever, used in its entirety for management decision-making. In developing an environmental impact statement for harvesting a forest stand, specialists from each of the subject domains (timber management, plant ecology, wildlife biology, and others) would be asked to interpret probable effects of the treatment. Summaries of the interpretations would form the environmental impact statement.

Intelligent geographic information systems. The chief limitations of conventional GISs for NRM or studies of landscape ecology are that relations among landscape elements cannot be interpreted without the intervention of human experts. Furthermore, many of the GISs currently available require considerable familiarity and expertise by the user, a problem that has greatly reduced acceptance and use of GIS, as it has for much of the simulation modeling technology available to practitioners.

AI techniques, however, particularly object-oriented programming and rule-based reasoning, have allowed the development of intelligent geographic systems (IGISs), which consist of a conventional GIS with (i) the added capability of interpretation and (ii) a user interface that guides efficient application of the system. IGIS is a special form of intelligent database management, which is a branch of AI (*21*).

An IGIS contains the same four components as a conventional GIS. The object-oriented programming of the IGIS, however, binds data and related procedures into separate classes of objects and manipulates them as such (*1, 22*) (Fig. 4). Each object is defined by attributes (values for variables) and procedures (methods for manipulating the attributes). Objects communicate by sending messages to one another, which results in some type of response in the data theme; for example, initiation of a procedure or change in value of a particular variable. This dynamic message-passing provides interpretative capability. Communication within and among objects is effectively controlled by a supervisory rule base, which is also represented as an object. This approach eliminates the nested, procedural method associated with conventional programming. The rule base contains knowledge about relations among data themes as well as knowledge about how to use the system. The use of a conventional GIS would require the human expert to have both types of knowledge.

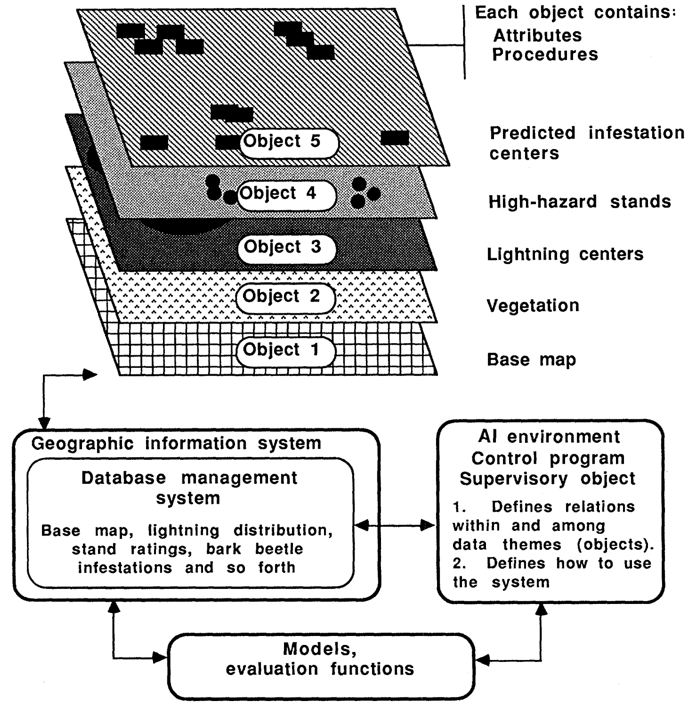

Fig. 4. Schematic that illustrates the components of an IGIS that uses object-oriented programming techniques and rule-based reasoning to interpret within and among landscape data themes.

An example of the usefulness of IGIS methodology involves research on the association of a natural disturbance and herbivory by bark beetles (Coleoptera: Scolytidae). Coulson *et al.* (*23*) hypothesized that the distribution, abundance, and size of bark beetle infestations in the southern United States are a function of the interaction of several factors, which include the pattern of lightning strikes for the region, landscape structure, forest stand structure, weather conditions, and the background population levels of the insects. Bark beetles often colonize a lightning-struck host; in some cases multiple tree infestations develop as a result of subsequent population growth, immigration, or both. This circumstance is most likely in certain classes of forest stands (termed "high hazard") and when weather conditions for beetle growth and development are optimal. Taken collectively within a region, the patches in forest stands created by activities of bark beetles can influence both landscape structure and forest management practices. The generalized structure of an IGIS for this association is shown in Fig. 4. There are five basic data themes (objects): base map (the coordinate system for the landscape area, for example, the pine forest region of east Texas), vegetation (host type for the bark beetles), lightning centers (available from thunderstorm radar maps or lightning detection instrumentation), centers of high-hazard stands (based on information on forest-stand inventory and characteristics of the landscape), and predicted infestation centers. Each data theme has associated with it attributes, procedures, and rules as described earlier. The basic premises underlying the hypotheses in question are

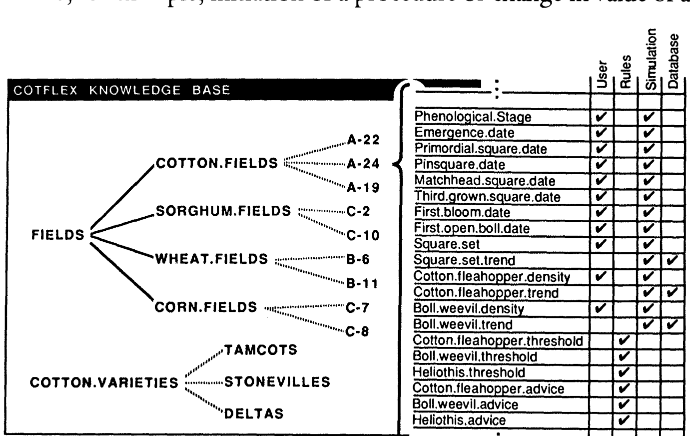

Fig. 3. A portion of the COTFLEX (*5, 12*) knowledge base showing a subset of the attributes of a cotton field and the sources for the values of those attributes. For example, A-24 is a specific instance of a cotton field and includes advice about how to control pests in a field. A-24 is derived from rules that depend primarily on the values of the attributes shown.

contained in the supervisory rule-base object (in the AI environment section of Fig. 4). This rule base defines the relations within and among the various data themes to provide interpretation and integration that are not available in conventional GISs. An IGIS approach to the bark beetle–lightning scenario, then, permits (i) testing of the basic hypothesis that landscape disturbance and insect herbivory are related, (ii) examination of the effect of bark beetle infestations on forest landscapes, and (iii) development of a tool that predicts distribution and abundance of infestation centers.

AI Models of Animal Behavior and Ecology

Although AI methods contribute to better decision-making and more effective NRM, AI techniques also offer new approaches to developing deep-knowledge models of ecological processes at the organismal level. These newer methods focus on the representation and simulation of animal behavior and on the interactions between the animal and the environment. The term "AI model" is used to emphasize that such models embody both theory (about how animals and components of ecological systems function) and implementation of theory (usually in the form of a computer program) (*24*). Thus the main emphasis of AI modeling is to explain system behavior in terms of computation (*25*).

The approach is to use the "object-oriented paradigm" described above to model interactions among organisms, interactions between organisms and their environments, and the internal motivational systems whose interactions lead to observable behavior in an organism. In addition, each component of a behavioral or ecological system may be modeled with appropriate mechanisms (which may include some combination of rule bases, hierarchical decision trees, or evaluation functions). The use of AI tools to represent complex data (dynamic data structures in particular) and to manipulate them with search techniques for pattern matching fosters this multilevel approach for constructing models. Simulation with such models provides new means for evaluating emergent behavioral and ecological properties at the individual and population levels.

These modeling techniques have several advantages over traditional methods for developing deep-knowledge models of natural resource processes: (i) a rich repertoire of data structures, both dynamic and static, to represent behavioral states; (ii) sophisticated procedures to manipulate these data structures; (iii) event-driven rather than time-driven control of processes; and (iv) dynamic linkages among components of the model rather than the static linkages found in traditional systems and network models. The application of the concepts in ecological modeling is discussed below.

Applications to animal behavior and ecology. Some aspects of animal behavior are well suited for modeling with AI techniques, particularly forms of behavior with a small number of discrete states. Changes in behavioral state can be viewed as results of decision processes. The task of the researcher is to develop models of those decision processes that demonstrate appropriate behavior. In motivational and physiological systems such as hunger, safety, reproduction, sociability, thirst, and temperature regulation, each system has its own decision-process structure. These systems then interact to produce a decision that results in observable behavior of the organism. With such "behaving" components, the object-oriented approach may be used to simulate emergent behavior of the organism and explore alternative hypotheses about how such components should interact.

Object-oriented programming offers a new perspective for modeling animal-environment interactions. The traditional way of posing a problem for computer solution in ecology is to establish basic data structures for the problem and then to create procedures to manipulate these data. This method is an artificial way to dissect a biological problem. The object-oriented approach allows definition of a problem in terms of actors (objects) and communications (messages) between them (*26*). Each actor has an internal state (usually a dynamic data structure) and a set of rules or processes (internal procedures) by which to respond to messages and modify its state. There is a fairly direct correspondence between objects and their messages on one hand and the organisms, environmental components, and the interactions of our conceptual models on the other. This correspondence allows development of programming models that closely match conceptual models of biological systems.

Models of the behavioral processes of deer relative to habitat use and models of deer-habitat interactions are being developed to test applications of these techniques. The deer-habitat model is based on detailed data on (i) forest stand structure collected from the viewpoint of wildlife management and (ii) deer behavior from extensive radio-tracking studies (*27*). The approach of the model is to consider each deer and each forest stand as separate objects. A deer communicates with other objects by sending and receiving messages. For example, when a deer enters a particular forest stand, it announces its presence and "queries" the stand about available resources (such as browse or cover attributes). The deer may also send a message to the stand by removing a quantity of browse (eating); the stand would then update its "memory" as to the amount of browse remaining. Simulation involves interactions among components by means of such messages.

Although the technique of assigning active roles to inanimate objects may seem unusual, this formal exchange of information provides a workable model of separate objects with specific types of asynchronous communication between them. The state of each object depends on the sequence of internal responses to the history of communications received from other objects in the simulation. Each object may be as simple or as complex as necessary to effect the required type of behavior; other objects see only the external messages sent by the given object. In particular, an object can have an internal memory that is modified by messages received and that affects messages generated.

New conceptual benefits from AI modeling of natural phenomena. Perception of time is a critical factor in development and use of simulation tools. Modern approaches to simulation of natural systems are based on a concept of time that arose relatively late in human intellectual development (about the 14th century). Before then, time was measured by the occurrence of natural events in daily, lunar, and annual cycles (*28*). Perception of time was "event-driven." Since the introduction of the clock, however, time has been parceled into many discrete units that have no direct relation to the events and processes of biological systems. This "new" concept of time has allowed definition and measurement of rates essential to modern simulation techniques. Nevertheless, animal-environmental systems are event-driven, whereas simulation techniques depend on a rigidly structured time scale. This circumstance strongly constrains conceptual approaches to modeling.

In AI modeling the time-lock simulation mode commonly used in ecology can be avoided and event-driven models can be constructed that more closely reflect the natural systems they represent. Each component of such a model operates as an independent process with its own internal structure, dynamics, and time scale. The component processes, or objects, interact with one another by communicating with messages. Exchange of a message between two objects constitutes an "event." The components still have access to "time" and are driven not by it but only by interactions with other objects. The plant that produces a leaf operates on a time scale that is very different from that of the deer that browses on it; however, clear-cut communication obviously occurs between them when the deer bites off the leaf.

Traditional approaches in systems simulation and network modeling provide for interconnected system compartments or network nodes. These connections are an integral part of the model definition and establish a static linkage for the duration of simulation. In contrast, object-oriented programming uses dynamic linkages; links (messages) between components are created and destroyed dynamically as functions of the states of the components at various points in the simulation. Such a representation is much closer to our perceptions of interacting animals than is the traditional systems approach.

An AI approach to modeling allows consideration of systems with multiple time scales that affect multiple processes within each system; it makes possible dynamic linkages among components and permits the simulation of "complex dynamical systems" (*29*). Complex dynamical systems adapt to changing environments. Although they have complex behaviors that arise from interactions of their components, the rules that govern those interactions are fairly simple. This view of ecological systems provides a powerful tool for exploring the effects of alternate strategies (represented by alternate properties of components or interaction rules) on development of system behavior.

Epilogue

In the preceding sections three uses of AI were examined: IEXS, IGIS, and AI modeling. The purpose, benefits, and beneficiaries of each AI application are somewhat different and reflect a range in interest from problem-solving and decision-making to landscape ecology and modeling of animal populations. Both applied problems in NRM and basic scientific issues can be addressed. The types of products that can be developed by using AI techniques may be of use for resource managers and research scientists. AI applications in NRM are just beginning to be explored.

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