

# APPLICATION OF ARTIFICIAL INTELLIGENCE TO RISK ANALYSIS FOR FORESTED ECOSYSTEMS

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## ABSTRACT

*Forest ecosystems are subject to a variety of natural and anthropogenic disturbances that extract a penalty from human population values. Such value losses (undesirable effects) combined with their likelihoods of occurrence constitute risk. Assessment or prediction of risk for various events is an important aid to forest management. Artificial intelligence (AI) techniques have been applied to risk analysis owing to their ability to deal with uncertainty, vagueness, incomplete and inexact specifications, intuition, and qualitative information. This paper examines knowledge-based systems, fuzzy logic, artificial neural networks, and Bayesian belief networks and their application to risk analysis in the context of forested ecosystems. Disturbances covered are: fire, insects/diseases, meteorological, and anthropogenic. Insect/disease applications use knowledge-based system methods exclusively, whereas meteorological applications use only artificial neural networks. Bayesian belief network applications are almost nonexistent, even though they possess many theoretical and practical advantages. Embedded systems -that use AI alongside traditional methods- are, not unexpectedly, quite common.*

**Keywords:** *Artificial intelligence risk analysis forest ecosystems, hazard, disturbance.*

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## 1 Introduction

Disturbance events are endemic to all complex systems, whether the system is natural or man-made. Complex systems (e.g. ecosystems), that people are dependent on, consist of many, interacting subsystems. When one or more of those smaller subsystems (or their interconnections) fails or behaves aberrantly, it often causes the behavior of the overall ecosystem to change. Such an ecosystem change, then, percolates through to the larger system composed of human populations together with this ecosystem. Many of the institutions (e.g. economic, biological, social, and cultural) inherent to human populations' success and prosperity thrive in a static environment where current conditions are presumed representative of future conditions. Because unpredictable disturbance events modify the trajectory of conditions over time, they can disrupt the status quo of human populations. Therefore, populations must continually exist with uncertainty surrounding future events and their impacts. Life is inherently risky.

Because disturbances cause changes in future scenarios, that differ from status quo expectations, disturbances are often viewed negatively as *loss events*. That is, human populations incur some penalty for disturbances - for being unprepared, "I didn't expect it to rain today, so I didn't take my umbrella. It rained. I got wet. Getting wet greatly reduced my physical comfort level." Disturbances to forest ecosystems are not implicitly "bad" for those ecosystems per se, but they do change their character and the benefits derived from them by human populations. These benefits include commodity values (e.g. timber), amenity values (e.g. scenic vistas), and other ecosystem values (e.g. biodiversity). Even though some disturbances can have beneficial impacts from a human standpoint -for example, wildlife openings created by small, intense fires- the unpredictable nature of disturbances disrupts human expectations of future conditions, and results in a change of benefits and creates losses for those human institutions that expect certain benefits at certain points in time and space. Therefore, for the purposes of risk analysis in this paper, disturbances are cast as "loss events" and viewed in a negative light. As Lackey (1997) noted, risk is almost universally treated as *adverse*, even though ecological change can be either desired or undesired, depending on the value system in place.

Forest ecosystems are subject to a variety of disturbances, including fire, drought, insect and disease attacks, windthrow and breakage, air pollution, rain and surface water acidification, snow/ice damage, threatened and endangered species viability, and other small-scale disturbances. Some of these events are natural and some are anthropogenic. Insect and

disease problems have received the greatest attention due to their ubiquitous presence in all types of forests and in all locations; fire is probably the next most important disturbance. Nevertheless, depending on the site, any one of these disturbances can assume the highest priority due to frequency and/or severity. As human populations manage forests and plan for the future, it is important to know how much of a potential problem these disturbances offer, both now and for future generations. That is, “How much are we likely to lose from a potential disturbance?”

The terms “risk” and “hazard” are often used synonymously in the literature (which is consistent with most dictionary definitions), but they are also treated quite vaguely in many cases. Nevertheless, I will try to couch past reports within a more rigorous definition of risk. For this paper, I will adopt the same definition used by others (e.g. Schmucker, 1984; Beer and Ziolkowski, 1995; Lackey, 1999) who treat *risk* as an attribute of a loss event (disturbance), which is composed of 2 components: *potency* (or cost, the severity and extent of the loss event) and *chance* (the likelihood of the loss event). This is also consistent with an actuarial definition that treats risk as expected value loss, where the expected value of a loss event,  $E(X_i)$ , is the product of the probability of the event,  $Pr(X_i)$ , and its associated cost  $C(X_i)$ . For  $n$  mutually exclusive events  $X_1, X_2, \dots, X_n$  such that all the  $Pr(X_i)$  sum to 1, the total loss is then the sum of the individual expectations  $E(X_i)$ . When we apply this definition to past work, however, we will see that different approaches to risk analyze different things. Some examine only potency, and do so in terms of severity only or extent only or both, e.g. the intensity (mortality level) of a pest outbreak versus the geographic spread of the outbreak. This assessment of the undesirable effect is often termed “hazard” (q.v. Beer and Ziolkowski, 1995). In the review that follows, we find that some researchers analyze risk as the *likelihood* of a loss event only, wherein either an event probability is estimated or predisposition for a loss event is assessed. Still other examples provided demonstrate a combined risk assessment that fuses potency and chance, without any explicit actuarial mathematics. While all these different flavors of risk analysis may seem different and lacking commonality, a unifying and underlying objective is to “assess the negative consequences of an uncertain and undesirable event.”

Risk analysis can be applied to either current situations or future conditions. Both types of quantitative estimates are difficult to produce, owing to a lack of data, uncertain events, and complex resource interactions. Therefore, artificial intelligence (AI) methods -which are effective in data-poor environments, can handle uncertainty, and use heuristics to encapsulate complexity (Schmoldt and Rauscher, 1996)- appear well suited to risk analysis problems.

This paper examines several AI techniques for analyzing risk, fully recognizing that the biological science that gives a risk analysis substance and the social context that drives the inquiry into risk analysis (and its interpretation) are outside the scope of this review. AI applications of risk analysis are diverse, due to the breadth of forest-related resources. It would be unrealistic to try to capture them all in a few pages, but this review will rather attempt to identify some key issues that characterize risk in managed ecosystems and how AI methods have attempted to address those issues. The objectives here are two-fold: (1) provide a synthesized overview of the literature in this important area of forest management and (2) describe how the attributes of AI methods make them good candidates for assessing risk. Before delving into the various disturbances addressed by AI risk applications, brief reviews of several important AI methods are provided.

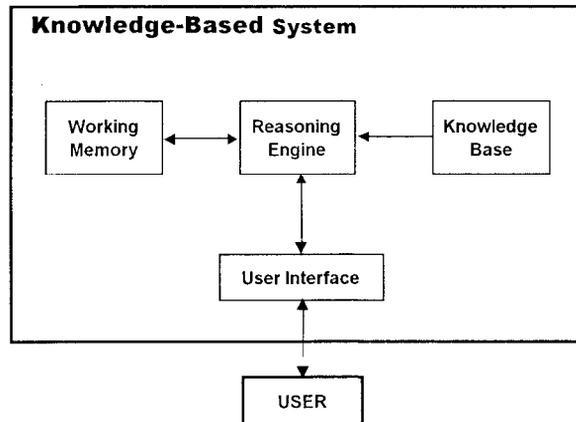
## **2 Artificial Intelligence Methods**

Artificial intelligence methods include a wide variety of computational and algorithmic approaches to problem solving. Their common theme, however, is that they attempt to provide computers with a capability to solve problems in ways that have traditionally been the purview of humans. This means that AI methods incorporate such human cognitive abilities as: reasoning with anecdotal information and best-guess judgment (knowledge-based systems), using vague and commonplace descriptions of objects and events (fuzzy logic), making decisions based on learned patterns with little explicit knowledge or rationale (artificial neural networks), and dealing with large amounts of uncertain, yet interrelated, data and information (Bayesian belief networks). While it is possible to combine these different methods (e.g. fuzzy rule bases and fuzzy neural networks) or to augment with expanded capabilities (e.g. knowledge-based systems that explicitly handle uncertain and inexact information), this overview will treat each method separately and only mention extensions to the standard methods when reviewing particular applications later. Each of the following subsections provides a brief introduction to these techniques in turn.

### ***2.1 Knowledge-Based Systems***

A knowledge based system (KBS) is a computer program capable of simulating that element of human knowledge and reasoning that can be formulated into units of knowledge so that a computer can approximate human ability to solve problems (Waterman and Hayes-Roth, 1978; Barr and Feigenbaum, 1982; Schmoldt and Rauscher, 1996). KBSs are distinguished as a subset of AI systems by the fact that they make domain knowledge explicit and separate

from the remainder of the system's "reasoning" mechanisms (*reasoning engine*). This separation of knowledge and algorithms is depicted in *Figure 1*, where the *knowledge base* contains domain-specific knowledge and the reasoning engine operates on that data structure to make inferences and draw conclusions. The *working memory* contains data and information pertinent to a specific problem at hand. The reasoning engine then applies the knowledge base to the contents of working memory for problem solving



*Figure 1.* A typical knowledge-based system "reasons" about a particular problem described in its working memory by applying the expertise resident in its knowledge base.

There are numerous techniques for knowledge representation, but traditionally the most common one is the use of *condition-action rules*—see Luger and Stubblefield (1989) and Schmoldt and Rauscher (1996) for a comprehensive review of knowledge representation techniques. Condition-action rules are IF-THEN statements where the consequent action(s) are performed if the premise condition(s) are true, for example, "IF site = sandy AND tree\_height < 20 AND previous\_winter = mild THEN insect\_hazard = high." This method of knowledge representation is popular because each rule is modular and contains a "chunk" of domain knowledge. KBS programmers find rules easy to program, and experts are often able to express their heuristic knowledge in an IF-THEN format.

*Working memory* is like the short-term memory of a KBS. It contains assertions about the problem currently being investigated. These assertions may be obtained from the user (via queries), from external programs, from a real-time process, from external data files, or inferred from other facts already known. Usually a *closed world assumption* is involved, i.e. only those assertions that are present in working memory are true, all other possible assertions about the state of the world are assumed false.

The knowledge base and working memory are passive entities, whereas the *reasoning engine* navigates through the knowledge base and registers established assertions in working memory. Navigation is performed by the particular control strategy the reasoning engine employs. A control strategy determines the order in which knowledge base elements (e.g. rules) are examined to reach a problem solution. In a rule-based knowledge representation, the inferencing method is usually *modus ponens* and rules are selected for evaluation either by the content of their premise conditions (data-driven control) or by their consequent actions (goal-driven control). Details of how the reasoning engine operates are determined by the knowledge representation method use, what types of assertions must be made, and the overall problem-solving methods that are applied.

*Expert systems* are distinguished from KBSs in that the knowledge base of an expert system is not derived from generally available (public) knowledge (e.g. textbooks, etc.), but comes from expert specialists in a problem domain and their “private” knowledge of a field. The distinction between KBSs and expert systems is fuzzy at best because the concept of expertise is, itself, not well defined. Consequently, I will generally use the term KBS inclusively, and not worry about the distinction between KBSs and expert systems.

## **2.2 Fuzzy Sets and Fuzzy Logic**

There are several ways in which one can view the nebulous concept of “uncertainty.” Whereas statistical probability theory treats uncertainty as randomness or likelihood, it may be more appropriate to consider the *meaning* of information instead. Many of our descriptions of what we know and how we use our knowledge can only be specified in *vague* terms. For example, “short person” and “tall person” are vague descriptors because they are non-explicit and subjective. Zadeh (1978) developed *possibility theory* as a way to treat vague, yet meaningful, information and as an alternative to probability theory’s treatment of random events. Possibility theory is an extension of probability theory wherein the “excluded middle” principle is relaxed. That is, an event can belong partially to both the set “true” and the set “false.”

*Fuzzy sets* were introduced by Zadeh (1965) to represent possibility measures. Formally, let  $S$  be any set (e.g. the possible heights of trees, in meters),  $s$  an element of  $S$ , and  $F$  a *fuzzy subset* of  $S$  (e.g. heights of tall trees). Then the possibility that  $s$  is in  $F$  (i.e. that a particular height, say 30m, is in the set of heights that are interpreted as “tall” for a particular tree species) is defined by a membership function  $q$ . The function  $q$  maps all heights onto the interval  $[0,1]$ . “Tall” is then referred to as a *fuzzy member* representing the fuzzy set  $F$ . A tabulation of  $q(s)$  for some values of  $s$  in  $S$  is presented in *Table 1*.

In keeping with the idea of an algebraic number, we can add, subtract, multiply, and divide fuzzy numbers that are defined over an arbitrary integer base. Such mathematical manipulations of fuzzy numbers were used by Schmoldt (1991) for a qualitative model of soil-plant-atmosphere interactions using the fuzzy arithmetic described by Schmucker (1984) for risk analysis. More often, however, fuzzy sets are used to create fuzzy rule bases.

height $s$ in $S$ (meters)	membership $q(s)$ in “tall”
15	0.1
17.5	0.2
20	0.4
22.5	0.5
25	0.7
27.5	0.8
30	0.9
32.5	0.9

*Table 1. From possibility theory, all possible heights of trees have an associated possibility, defined by  $q$ , that indicates each height's membership in the fuzzy set “tall”. All heights less than those listed are assumed to have a membership value of 0 and, similarly, all heights greater than those listed are assumed to have a membership value of 1.*

The calculation of belief in a hypothesis  $H$  based on a rule of the form  $A$ : IF  $E$  THEN  $H$  proceed as follows. First, any premise  $P$  in  $E$ , will be of the form  $X$  is  $F$ , which means that the variable  $X$  is in the fuzzy set  $F$ , for example,  $X$  might be the average height of the dominant trees in a stand and  $F$  the fuzzy set *tall*. The interpretation of that clause would be that “average tree height is tall” and the membership value  $q$  associated with the average height, i.e.  $X$ , and the set *tall* would represent the belief that the average tree height is tall, i.e.  $q(X)$ . Second, two clauses joined by *and* have a combined belief that is the minimum belief held by the component clauses. In the case of a disjunction of clauses (joined by *or*), the combined belief is the maximum of the component clauses. Third, when *not* is applied to a clause, the resulting belief is 1 minus the membership value of the clause. In general, if  $F$  is the fuzzy set *tall* and  $F'$  is the fuzzy set *not tall*, then *not tall* has the membership function  $q(F') = 1 - q(F)$ . Belief in the final hypothesis  $H$ , then, is the combined belief of all the evidence  $E$ . In some cases, however, the rule  $A$  may have a belief value attached to its inference (either a numerical value in the range  $[0,1]$  or a fuzzy number) that is used to modify the belief contribution of the evidence. Then, the belief in the hypothesis  $H$ ,  $B(H)$ , equals  $B(E) \times B(A)$ .

There are some advantages to the fuzzy set approach. The ability to interpret and utilize natural language terms such as “many”, “large”, “tail”, or “more or less” seems consistent with the way that people communicate information and knowledge to each other. Also, fuzzy sets are an example of what is referred to as a *multi-valued logic*, that is, a single term can have several values simultaneously, each one with its own belief level. For example, in addition to the fuzzy set “tall”, we may also have a fuzzy set “above average”. The membership of 20m in the fuzzy set “above average” might be 0.8, while it is 0.4 in the fuzzy set “tall.” So, the height, 20m, could be interpreted as both “above average” and somewhat “tall”. By capturing vagueness and permitting multiple-valued entities fuzzy sets mirror some of the inherently inexplicit ways we reason about our world.

### ***2.3 Artificial Neural Networks***

Despite substantial success, KBS models of intelligent behavior have been criticized on theoretical as well as practical grounds (Allman, 1989). The KBS paradigm represents a top-down approach to reasoning. This perspective assumes that reality can be described by abstract symbols that represent objects and their relationships to one another. Thought is based on symbols and, indeed, human consciousness is almost synonymous with language, the mental manipulation of symbols (Smith, 1985). While high-level, abstract thinking can often be reasonably formulated in this way (e.g. expert system knowledge), this symbolic model begins to break down when applied to sensory level activities, such as speech recognition, vision, and pattern recognition. KBSs also fail when: problems are highly quantitative, have no well-reasoned or explicable model relating input information to output decisions, or no human specialists exist.

Many of the models and techniques developed in AI borrow from naturally occurring models of complex system organization. The human brain is often used as a model, but cultural/social systems and biological systems (e.g. an ant colony) have provided valuable insights for AI also. Artificial neural networks (ANNs), also referred to as parallel distributed processing by Rumelhart and McClelland (1986), follow this natural/artificial association quite closely by modeling brain nerve cells and their interconnections. The seminal work of developing mathematical models to simulate neural networks was conducted by Hebb (1949).

In response to the limitations of symbolic processing, some AI researchers have turned to recent advances in neurophysiology in their search for more useful models of some aspects of human thought processing. These models signify a bottom-up description of thinking, rather than top down. An artificial neuron is depicted in *Figure 2*. In general, a neuron

environment consists of an input vector  $\mathbf{X} = x_1, x_2, \dots$ , a weight vector  $\mathbf{W} = w_1, w_2, \dots$ , a summation block that combines the inputs and weights, and an activation function  $f$  that transforms the weighted sum into an output signal. The net result of applying the weights  $\mathbf{W}$  to the inputs  $\mathbf{X}$  is the value,  $net = \mathbf{XW}^T$ . An activation function  $f$ , usually a nonlinear function or a threshold function, is applied to the value  $net$  to produce an output value,  $OUT = f(net)$ . Several of these neurons may be placed within a single layer of a network to create what is often called a perception (*Figure 3a*). When perceptions are organized into multiple-layer networks (*Figure 3b*) and utilize a nonlinear activation function, they become quite powerful computationally (Wasserman, 1989).

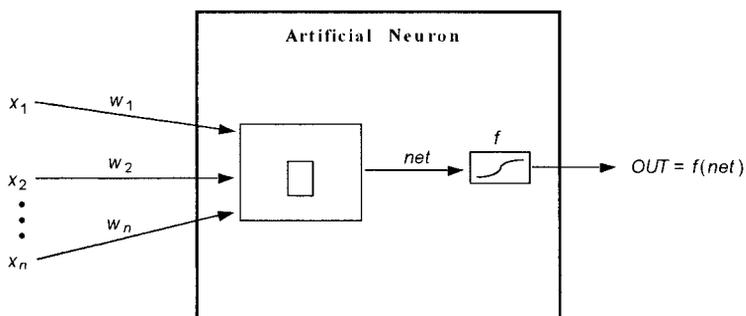


Figure 2. A single artificial neuron contains inputs  $X$ , weights  $W$ , a summation function, and an activation function  $f$  to produce an output response,  $OUT$ .

The last illustration (*Figure 3b*) represents the general architecture of a multiple-layer neural network. For a network to operate correctly, it must be trained by adjusting its weight arrays. There are two general types of training methods: supervised and unsupervised. In supervised training, each input vector is paired with a target output vector to produce a training pair. As each input vector is applied to the network, its output is compared to the target and an error is calculated. This error is used to adjust the weights so as to minimize the error. When the errors for the entire training set are acceptably low, then the network has been trained. Unsupervised training requires no target vectors, only input vectors. The training algorithm modifies weight vectors to produce output vectors that are “consistent.” Hence, similar input vectors are organized into classes designated by the output patterns. In addition, some transformation may need to be applied to convert the output patterns into intuitively understandable classes. Just as there are many different architectures for neural nets, there are also numerous different training algorithms that can be applied to them. This diversity in architectures and training methods permits a rich and varied repertoire of applications.

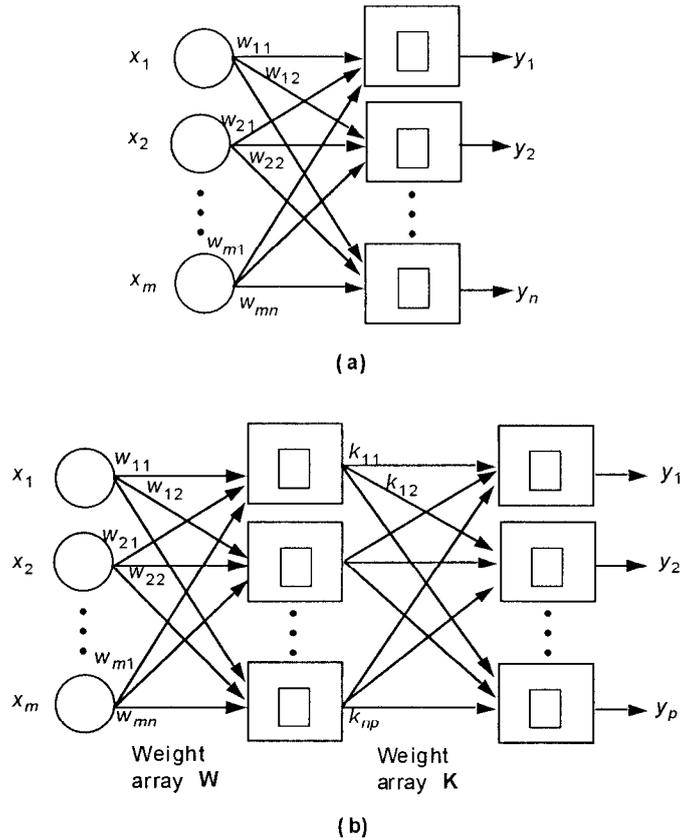


Figure 3. A number of processing units can be arranged into a single layer network (a), termed a perceptron. More complex and useful networks contain multiple layers (b).

In forestry, empirical statistical models have traditionally been used to relate dependent and independent variables. ANNs can perform the same relationship-finding task, although in a much different way. Despite the past and continued usefulness of traditional statistical models, ANNs have a number of advantages that have proven valuable. In particular, ANNs require no distributional assumptions regarding the data, can discern nonlinear relationships as easily as linear ones, and require no explicit specification of a mathematical model relating input variables to output variables. On the other hand, ANNs possess some significant disadvantages compared to statistical models. First, ANN training uses an iterative process and hence requires much longer to reach a solution than a typical maximum likelihood estimation procedure used by linear statistical models. Second, because training is iterative, there is no guarantee that an optimal solution has been reached; often local minima are selected. Third, the final ANN architecture and weight matrices can appear very much like a

black box, providing little insight into any true relationship between input and output. Fourth, when ANNs are applied to a specific problem, there are no confidence levels associated with a prediction, as with statistical models. Despite these limitations, ANNs have been found to be superior to logistic regression and discriminant analysis in many instances (e.g. Salchenberger *et al.*, 1992; Tam and Kiang, 1992; Hill *et al.*, 1994; Tomlins and Gray, 1994; Ruisanchez *et al.*, 1996; Marzban *et al.*, 1997). They usually outperform these classification models (Bansal *et al.*, 1993) when one or more of the aforementioned situations hold, i.e., unknown or non-normal data distributions exist, relationships may be complex and involve many independent variables, linearity of the relationships is unknown (Bansal *et al.*, 1993; Hill *et al.*, 1994) or theoretical/functional models are not apparent (Hill *et al.*, 1994). The review of ANN applications in business and finance by Hill *et al.* (1994) demonstrates broad superiority of ANNs over regression, logistic regression, discriminant analysis, and nonlinear regression. ANNs are not universally better than statistical models, but do possess distinct advantages in some circumstances.

#### **2.4 Bayesian Belief Networks**

Much of our understanding of how the world works uses cause-effect models (or influence models). That is, the behavior of any phenomena is understood by considering the influences that other phenomena/events have upon it. For example, we might model tree growth as influenced (caused) by available light, soil moisture, and soil nutrients. The rules that are often used in KBSs -if A and B, then C- are one way of representing and reasoning about these cause-effect relationships,

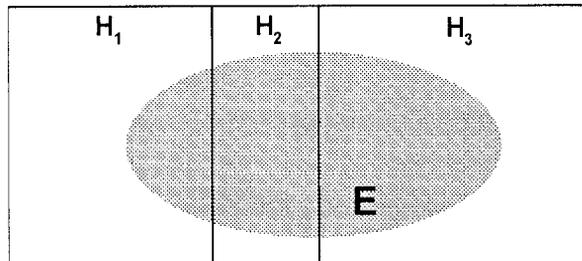
While measures of uncertainty, e.g. certainty factors (Shortliffe and Buchanan, 1984) can be used within a rule-based structure (e.g. Schmoldt, 1987) interpretation of the rules and interpretation and propagation of the uncertainty measures may not always coincide very well. Furthermore, it is only possible to reason in one direction using rules, whereas it is often useful to hypothesize a *cause* given some knowledge about the presence of an *effect* (reasoning in an effect  $\rightarrow$  cause direction). Finally, if information about A is missing, then the rule “if A and B then C” cannot be used. Bayesian belief networks (BBNs) overcome these limitations of the rule-based formalism by encoding probabilistic relationships among variables in a graphical model (Heckerman and Shachter, 1995). BBNs began with Pearl (1988), who first applied Bayesian probability theory to an influence graph representation of knowledge to allow bi-directional reasoning with uncertainty and subjective knowledge.

The use of Bayes' theorem requires an a priori belief (also called a *prior probability*),  $P(H_i)$ , in each hypothesis and it also requires conditional probabilities,  $P(E/H_i)$ , of the current evidence,  $E$ , given each possible true hypothesis. This relationship between evidence and hypotheses can be seen in *Figure 4*. Here, we have three mutually exclusive hypotheses  $H_1$ ,  $H_2$ ,  $H_3$ . Given some evidence,  $E$ , each of these hypotheses has some probability of being true. Ultimately, the value we seek is called a *posterior probability* (it results from an updating of the prior with the conditional information) and is represented by the expression,  $P(H_i|E)$ . In an actual KBSs, the posterior probability is usually an inference of some sort relating the evidence to a particular hypothesis, e.g. an if-then rule. Mathematically, this can be calculated as:

$$P(H_i | E) = \frac{P(E | H_i) \cdot P(H_i)}{\sum_{k=1}^n P(E | H_k) \cdot P(H_k)} \quad (1)$$

where the denominator is precisely  $P(E)$ . Using *Figure 4*,  $P(H_i)$  is the percentage of the total area of the big rectangle occupied by the rectangle  $H_i$ , and  $P(E/H_i)$  is the percentage of the area in  $H_i$  that is shaded.

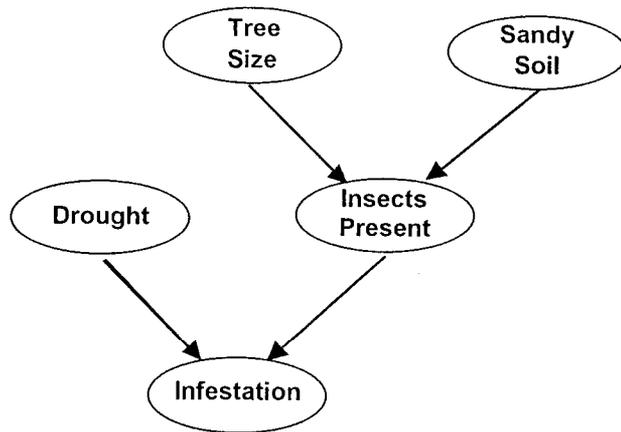
The variables of interest in a BBN are represented in a unidirectional, acyclic graph. This means that causation only goes one way and there are no feedback loops. Under these conditions, it is possible to arrange the network of causation so that any variable in the BBN is conditionally independent with a set of other variables. Independence among variables is essential for the application of Bayes Theorem.



*Figure 4* . Given three mutually exclusive hypotheses  $H_1$ ,  $H_2$ ,  $H_3$ , each has some probability of being true a priori, i.e. before  $E$  has been observed. The a priori probability of each hypothesis is reflected by its relative area within the total area of the rectangle. Each of these hypotheses has a different probability of being true under the condition of the evidence,  $E$ , being true. Therefore, with the observance of evidence,  $E$ , the focus is no longer the relative area of each hypothesis within the large rectangle, but rather the relative area of each hypothesis within the shaded oval.

While the example in *Figure 5* is rather trivial it illustrates how one might construct a cause-effect network. The variables *drought*, *tree size*, and *sandy soil*, each have prior probability distributions, whereas *insects present* and *infestation* have conditional distributions. Based on values entered for the former variables, probabilities will propagate and update belief in the latter variables. That is, the probability that an infestation is present can be projected given the other evidence  $P(\text{infestation} \mid \text{drought} \ \& \ \text{tree size} \ \& \ \text{sandy soil})$ . However, it might also be desirable to know  $P(\text{drought} \mid \text{infestation})$ , i.e., how likely it is that drought conditions are present given that an infestation has occurred. In that case, this network might be part of a larger network that links drought to fire danger risk, wherein an insect infestation might signal conditions conducive to an escaped fire.

BBNs enable one to utilize both subjective judgement (conditional probabilities) and existing data sources (prior probabilities). Their strong theoretical underpinnings make them attractive to management scientists and operations researchers familiar with decision-analytic techniques.



*Figure 5.* An influence graph illustrates the factors that might cause an insect infestation. Variables that are not directly or indirectly connected by links are conditionally independent.

### 3 Risk Analysis

As noted above, the literature on risk analysis in natural resources uses risk terminology quite loosely and ambiguously. Risk analysis in one instance may be termed hazard analysis in another, or may address only the *chance* component of risk without any consideration of *potency*. Consequently, it would be difficult to categorize risk applications solely using a particular analysis type. Rather, the following sections examine AI and risk in managed ecosystems according to disturbance type, including fire, insects/diseases, meteorological, and anthropogenic. There are other applications of AI and risk analysis for other disturbances, but these four represent the most common or the most important ones. A couple of instructive examples will be briefly described in each case, with an intent to illustrate the unique contributions that AI has made to risk analysis in each instance.

#### 3.1 Fire

In many parts of the world, fire is the major natural disturbance affecting ecosystems. Fire can produce short-and long-term impacts depending on frequency, intensity, and extent. It impacts not only forest resources, but often human populations directly when urban settlements extend into forested areas. Fire requires two elements: combustible fuels and an ignition source. Risk in this context considers either fuel loading/moisture or ignition likelihood or both factors. Fuel loadings and moisture effect are both risk potency and risk chance. Consequently, there is little commonality between risk terms and fire terms such as behavior, severity, occurrence, loading, moisture content, etc., which are the foci of fire risk analysis. Nevertheless, I will apply these risk terms to fire, adding clarifications as necessary. *Table 2* contains a summary listing of fire risk analysis applications.

The KBS reported by Kourtz (1987) for dispatching fire control resources in Quebec, Canada was one the first applications of AI in fire management. One component of this decision support system evaluates the post-detection fire behavior state and damage potential. This is accomplished using a variety of rule bases and existing simulation models of fire spread. The fire's potency is categorized into one of six behavior situations that partially determines subsequent dispatch of control resources. All the rule bases were developed from the expertise of highly skilled dispatchers; continual modification and evaluation over several fire seasons resulted in a dispatch system that rivaled these human specialists. The final system enables less-experienced dispatchers to apply the knowledge of the best fire

dispatchers, along with useful data bases and models, to react intelligently in stressful and time-critical situations.

Application	Analysis Type	AI Method(s)	System
<b>Fire</b>			
Fire situation classification (Kourtz, 1987)	Potency	KBS	Embedded
Wildfire occurrence prediction (Vega-Garcia et al., 1996)	Chance	ANN	Stand-alone
Fuel moisture prediction (Ball, 1997)	Potency	ANN	Stand-alone
Prescribed fire escape (Stock, 1996)	Chance	KBS	Stand-alone
Broad-scale fire severity (Lenihan et al., 1998)	Potency	KBS	Embedded

Table 2. Applications of AI to risk analysis for fire disturbances are summarized across several attributes, including type of risk analysis, AI method(s) used, and stand-alone/embedded system.

While some risk analyses treat risk factors using some extant theory of their importance and impact, other analyses attempt to generalize past data without regard to any underlying risk model. An example of this approach is daily wildfire occurrence prediction (Vega-Garcia et al., 1996) using historical data for specific zones within a provincial forest in Alberta, Canada. Rather than assigning likelihood to an event (chance), this study predicts actual event occurrence, but we will still refer to the prediction as *chance* (Table 2). A fire-weather index, zone area, and zone identifier were used as inputs to an ANN that was trained on data from 5 fire seasons and predicted fire or *no-fire*. Testing of the ANN on data from 2 other fire seasons gave 85% prediction accuracy for no-fire observations and 78% accuracy for fire observations. This type of model implicitly includes both fuel and ignition information, as they interact to determine fire occurrence.

In another application of ANNs, Ball (1997) attempted to predict fuel moisture from various environmental variables in the desert areas of the U.S. southwest. Separate ANNs were created to predict live- and dead-fuel moisture. Because this context is prescribed burning and fire behavior, fuel moisture prediction can be considered risk potency. Only 51 training samples were used, and when both ANNs were tested with these same data, they predicted moisture accurately in 92% of the cases. When splitting the same data set into training and testing sets, much lower accuracy was obtained. This suggests that their 92% value is an overestimate of the true accuracy. Given the small sample size, cross-validation techniques should have been used (Weiss and Kulikowski, 1991). No rigorous testing was performed with separate data sets, although a visual comparison was made between simulated

fuel-moisture maps and ANN-predicted fuel moisture maps. Again the results were not impressive. The authors suggested that the paucity of sample data and the use of a single fuel loading value for all fuel sizes greatly limited their results. Quantitative AI methods, such as ANNs, are not unlike other quantitative methods in that the method cannot compensate for poor data.

A related treatment of prescribed fire by Stock et al. (1996) analyzed the chance of escape of a prescribed burn. Their likelihood estimate uses a scale of 0 (no chance) to 100 (extreme escape danger), and is separate from any consideration of escape consequences (potency). Their KBS attempted to improve on a matrix model, previously developed and currently used by fire managers, by incorporating less explicit and more nonlinear aspects of the prescribed burning process. They used 3 test case comparisons with expert predictions to identify areas where their KBS could be modified/improved. In one of those cases, they found that the human expert was not separating chance (escape likelihood) and potency (escape consequences), as their KBS was attempting to do. By enabling fire managers to make this distinction in actual operations, they hope to place prescribed burning on a more objective decision-theoretic foundation, leading to better decisions.

A slightly different use of AI in risk analysis is the Dynamic Global Vegetation Model (DGVM, Lenihan *et al.*, 1998). This model simulates global change impacts from extreme fire events. The AI component does not directly predict either fire chance or potency, but rather generates a spatio-temporal distribution of vegetation classes using a rule base. These vegetation types are inputs to the fire simulation component of DGVM that projects fire behavior, severity, and effects. DGVM allows researchers and policy makers to predict changes in the occurrence and impacts of extreme fire events under different global climate change scenarios.

### ***3.2 Insects and Diseases***

The only natural disturbances more ubiquitous than fire are those that result from pathogens and insects. These disturbances occur in every forest type around the globe. Managed forests are particularly susceptible to their impacts due to unnatural management activities, limited host species genotypes, and uniform forest vegetation structure. Both insects and diseases are continually present in forests at sub-epidemic levels. When conditions are rife, however, mere presence can change to epidemic with dramatic, and often catastrophic, consequences. Risk analysis in this context assesses or predicts epidemic-favorable conditions. *Table 3* lists the AI applications covered below.

The first reported AI application in this area is the hazard assessment KBS of Schmoldt (1987). Here, stand hazard rating was an ancillary component of the PREDICT diagnosis KBS system that contained insect and disease knowledge for red pine (*Pinus resinosa*) in Wisconsin (USA). Ratings of low, moderate, or high hazard (along with a numerical estimate of hazard assessment reliability) are provided based on forest location and soil/site factors. Given forest conditions, this assessment provides a qualitative rating of the likelihood that an outbreak will occur.

Rust (1988) used a KBS to rate white pine (*Pinus monticola*) planting sites in the Pacific Northwest (US) according to their likelihood to develop white pine blister rust (*Cronartium ribicola*). In predicting future blister rust hazard, the system uses site factors and alternative host suitability. It also makes planting recommendations following hazard rating.

Application	Analysis Type	AI Method(s)	System
<b><u>Insects &amp; Diseases</u></b>			
Hazard assessment for red pine (Schmoldt, 1987)	Chance	KBS	Stand-alone
White pine blister rust hazard rating (Rust, 1988)	Chance	KBS	Stand-alone
Hemlock looper DSS (Power and Saarenmaa, 1995)	Chance & Potency	KBS	Embedded
Jack pine budworm DSS (Loh <i>et al.</i> , 1991)	Chance & Potency	KBS	Embedded
Mountain pine beetle population prediction (Downing and Bartos, 1991)	Chance	KBS	Stand-alone
Spruce beetle risk and hazard (Reynolds and Holsten, 1994; Reynolds and Holsten, 1996)	Chance & Potency	KBS	Embedded
Gypsy moth risk assessment (Potter <i>et al.</i> , 2000)	Chance & Potency	KBS	Stand-alone

Table 3. Applications of AI to risk analysis for insect and disease disturbances are summarized across several attributes, including type of risk analysis, AI method(s) used, and stand-alone/embedded system.

The decision support system (DSS) described by Power and Saarenmaa (1995) is unique in this overview in that the authors converted an existing DSS for hemlock looper (*Lambdina fuscicollis*) outbreak and impact prediction in Newfoundland (Canada). They used object-oriented techniques to create a more generic DSS framework that could be used/augmented for other forest pests. Their approach treats the decision-support problem in a more structured manner, while still making use of existing simulation models, data bases, and geographic information system (GIS) layers. In doing so, the authors highlight many of

the benefits of using AI approaches for risk analysis, such as object-oriented programming (originally developed in the AI research community).

The jack pine budworm (*Choristoneura pinus*) DSS reported by Loh et al. (1991) is similar in intent and function to the preceding system. Object-oriented techniques are used to link rule bases, a data base, and a GIS to manage jack pine (*Pinus banksiana*) forests in the Lake States (US) and Canada. One of the rule bases generates hazard ratings (low, moderate, high), that seem to incorporate both outbreak chance and impact (potency). Ratings are subsequently used to recommend management options.

Because pests exist continually in forests at endemic levels, it is important to predict when those levels might explode to epidemic levels. Downing and Bartos (1991) developed a KBS to predict mountain pine beetle (*Dendroctonus ponderosae*) population increases in lodgepole pine (*Pinus contorta*) stands in the western US. Climatic and site factors were used to predict the next year's brood level, along with a certainty-factor estimate of confidence in that prediction. Interestingly, the authors developed and used a knowledge-acquisition program to elicit knowledge from experts and then used commercial rule induction software to generate the rules. Separate rule bases were developed by each expert, and the experts then criticized the rule bases of their colleagues. This provides an interesting approach to incorporating multiple experts' knowledge into a KBS.

SBexpert helps manage spruce beetle (*Dendroctonus rufipennis*) outbreaks in south-central Alaska (US) spruce stands (*Picea* spp.). It contains rule bases to evaluate both chance (Reynolds and Holsten, 1994) and potency (Reynolds and Holsten, 1996) of spruce beetle outbreaks. Potency is treated as severity and is measured as percent basal area loss of spruce. SBexpert, version 2, is currently available (<http://www.fsl.orst.edu/usfs/sbexpert/>), and version 3 will include automated landscape-scale analysis using a GIS.

A web-based KBS (GyMEs) has been developed by Potter et al. (2000) to assess risk for gypsy moth (*Lymantria dispar*) outbreaks in the eastern US. While not the first web-based KBS, it is the first web-based risk analysis application in forestry. GyMEs assesses both potency of an outbreak and likelihood of an outbreak incident to arrive at a risk rating. Site factors, stand condition, disturbance history, and stand susceptibility are used to arrive at a qualitative estimate of risk, e.g. low, moderate, high.

### 3.3 Meteorological Phenomena

Weather events can cause regular and significant disturbances in forest ecosystems. Severe storms accompanied by strong winds, heavy rains, and ice formation can create major damage to trees and other forest resources. Weather patterns also interact with other disturbances to modify their occurrence or severity, such as fire (lightning strikes, drought) and air pollution (temperature inversions). In some regions of the world, weather events can be a major contributor to losses in the forest, and their spatio-temporal unpredictability makes them particularly risky. While there exists considerable research involving AI and meteorology (q.v. Christopherson, 1997; Gardner and Dorling, 1998), the number of studies with importance to risk in managing forests is much less. *Table 4* summarizes several example AI applications

Lakshmanan and Witt (1997) developed a fuzzy logic system to predict a critical precursor for severe thunderstorms. Their system automatically analyzes radar imagery and estimates fuzzy numbers from the data, which are then used in the fuzzy rules of a classifier. This classifier labels the critical regions in a radar image as either thunderstorm precursors, marginal precursors, or non-precursors. Their measure of success compares very favorably with other meteorological approaches to identifying thunderstorm precursors.

Application	Analysis Type	AI Method(s)	System
<b><u>Meteorological Phenomena</u></b>			
Detecting severe updraft conditions (Lakshmanan and Witt, 1997)	Chance	Fuzzy logic	Stand-alone
Damaging wind prediction (Marzban and Stumpf, 1998)	Chance	ANN	Stand-alone
Precipitation forecasting (Hall <i>et al.</i> , 1999)	Chance & Potency	ANN	Stand-alone
Localized precipitation forecasting (Kuligowski and Barros, 1998)	Potency	ANN	Stand-alone
Lightning strike prediction (Frankel <i>et al.</i> , 1995)	Chance	ANN	Stand-alone

*Table 4. Applications of AI to risk analysis for meteorological events are summarized across several attributes, including type of risk analysis, AI method(s) used, and stand-alone/embedded system.*

Certain regions of the world are prone to high-wind damage, which can have dramatic effects even in forested areas. Following prior work that compared ANN performance with that of

discriminant analysis and logistic regression (Marzban and Stumpf 1996; Marzban *et al.*, 1997), Marzban and Stumpf (1998) developed an ANN to predict the occurrence of damaging winds ( $> 25\text{m/s}$ ). Input data were taken from circulation patterns detected by the National Weather Service (US); the ANN model outputs a binary decision. Using a variety of performance measures, the authors found the ANN to be a reliable and discriminating predictor.

Accurate precipitation forecasts can identify the potential for heavy rains and associate flash flooding that can create extreme hydrologic events in watersheds and can damage man-made structures. Hall *et al.* (1999) developed 2 separate ANNs for rainfall prediction, one for precipitation occurrence probability and one for rainfall amount. Predictions were made for mean daily rainfall in a  $5000\text{ km}^2$  metropolitan area (presumably the same approach would work at the watershed scale). Both ANNs were extremely accurate in validation tests that covered daily precipitation amounts for a two-year period.

Because current quantitative precipitation forecasting models operate at a large scale, they are unable to make accurate localized spatio-temporal forecasts. Regression models have traditionally been used to interpolate for local regions and shorter time frames. Kuligowski and Barros (1998) developed an ANN to substitute for existing linear regression models. Tests conducted at four locations in the middle Atlantic region of the US showed that their ANN's accuracy performed comparably with forecasts generated using regression methods, especially for important heavy rainfall events.

Accurate spatio-temporal lightning strike prediction can aid forest managers to prepare for forest fires. Frankel *et al.* (1995) describe the development of an ANN to forecast lightning around the Kennedy Space Center in South Florida (US). Input data included a variety of detailed meteorological variables for the immediate area. Prediction results for 0-15, 15-30, 30-60, and 60-120 minute time windows within subareas of the Center were numerically equal to total-area predictions using a traditional linear-regression prediction model. Although the input data for their ANN were much more detailed than could easily be obtained in forested areas, the ANN's ability to forecast lightning events over small spatio-temporal scales holds promise for similar efforts in forests using readily available meteorological data.

### ***3.4 Anthropogenic Effects***

An ever burgeoning human population and its migration into, and adjacent to, previously sparsely inhabited forested areas is a stressor for forest resources. While populations can

disturb ecosystems at a distance through atmospheric pollutants, water pollution and misuse, grazing, greenhouse-gas induced climate change, and wildlife habitat disruptions, they can also impact ecosystems proximally by their land management and recreational activities. Such anthropogenic influences modify the course of ecosystem development and generate substantial risk, just as fire and insects. *Table 5* lists several AI applications for anthropogenic risk.

Application	Analysis Type	AI Method(s)	System
<b><u>Anthropogenic Effects</u></b>			
Lake acidification assessment (Lam <i>et al.</i> , 1989)	Potency	KBS	Embedded
Pesticide risk (Messing <i>et al.</i> , 1989)	Potency	KBS	Embedded
Recreation use prediction (Pattie, 1992)	Potency	ANN	Stand-alone
Air pollution forecasting (Nunnari <i>et al.</i> , 1998)	Potency	ANN	Stand-alone
Water quality monitoring (Varis <i>et al.</i> , 1993)	Potency	BBN	Embedded

*Table 5. Applications of AI to risk analysis for anthropogenic disturbances are summarized across several attributes, including type of risk analysis, AI method(s) used, and stand-alone/embedded system*

An interesting approach to assessing the extent of lake acidification is provided by Lam *et al.* (1989). The authors embedded a small KBS within a simulation environment (RAISON) to automatically select the appropriate acidification model and to analyze model results for anomalous behavior. In a comparison using 34 lakes in Quebec, Canada, the knowledge-based combined model of RAISON performed comparably to the individual component models. Proper application of simulation models is difficult, even for experienced users. A KBS that can elevate human performance in this task is a significant improvement over manual procedures.

While the KBS by Messing *et al.* (1989) deals with an agricultural application, it is worth mentioning briefly because it addresses pesticide risk - which is an issue in forestry also. Herbicide and pesticide applications to forests are relatively common in industrial operations, but little attention is often given to the potential damage those chemicals might cause for a pest's natural enemies, soil organisms, etc. The authors' rule base links to data bases, simulation models, and graphical tools to help the user estimate mortality for beneficial organisms.

Recreation over-use can have significant impacts, especially in wilderness areas. The ability to forecast visitor usage can enable managers to establish protocols and policies to

protect sensitive resources and to preserve the character of the wilderness. Pattie (1992) proposed an ANN to predict overnight backcountry stays in national parks and recreational visitor-days in national forests (US). Input variables selected for use in the ANN were intended to reflect the factors that drive recreation use/non-use. No information is available on the results of this development effort, but the proposed approach warrants inclusion here due to the anthropogenic risk (recreation) it deals with and to the AI technique selected.

Many forested regions are downwind from significant sources of atmospheric pollutants. These pollutants are known to have dramatic impacts on vegetation (ozone exposure) and water resources (nitrogen and sulphur deposition). Nunnari et al. (1998) used time-series data and an ANNs to predict short- and medium-range concentrations of ozone and nitrogen oxides. Their ANN provided improved forecasting over traditional statistical models (auto-regressive moving average with exogenous inputs), in particular for predicting ozone values exceeding a threshold.

Water resources health is an important aspect of forest ecosystems, Issues of monitoring system functioning and cost, in addition to risk attitudes and discount rates, were included in a BBN model of water quality monitoring (Varis *et al.*, 1993). The authors' model analyzed the costs and benefits of different monitoring systems under various scenarios of risk aversion, discount rate, and cost uncertainty. The flexibility of this type of model allows decision makers to form choices based on preferences (risk attitude) and exogenous variables (discount rate), in addition to scientific information (monitoring equipment).

## 4 Conclusions

While this overview of AI applications for risk analysis of forest resources does not review the literature comprehensively, it is, nonetheless, reasonably representative of the things that have been done. Consequently, there are some concluding observations that can be made regarding this area of research and application.

The integration of KBSs with simulation models is a natural, and not unexpected, approach toward risk analysis. Risk assessment often requires the use of quantitative values and many simulation models already exist for generating these values. KBSs, then, allow one to use that data more effectively by combining it with less quantitative information or to select the best modelling approach when several are available or to interpret model output.

There are several interesting observations apparent in the application summaries (Figures 2-5). Regarding analysis type, fire applications are split between chance and

potency, insect/disease applications always include chance (often combined with potency), meteorological applications are mostly concerned with event occurrence chance, and anthropogenic disturbance applications consider potency only. These particular emphases reflect obvious disturbance differences, e.g. anthropogenic disturbances exist, so the question of chance is moot and one wishes to predict severity and extent.

Regarding AI methods used, fire applications use both KBSs and ANNs, insect/disease applications use KBSs exclusively, meteorological applications use ANNs almost exclusively, and anthropogenic applications use a mixture of all four AI methods. The single-minded use of KBSs for insect and disease disturbances may be due to a lack of quantitative data and relationships regarding pests and forests. Being limited to qualitative information does not preclude the use of ANNs and BBNs, but it may bias researchers toward rules and away from more quantitative methods (Bayesian statistics, for instance). On the other hand, meteorology has historically dealt with large amounts of data, so the relatively exclusive application of ANNs to model quantitative relationships and to replace existing statistical approaches is not unexpected. Regarding system type, ANNs tend to be stand-alone applications. Although, because a trained ANN can be encoded as a single function call in a programming language, I would expect to see ANNs embedded in other software systems more often in the future. KBSs can be either stand-alone or embedded depending on whether software tools (e.g. simulation models, GISs) are available or needed. Hopefully, as future AI systems for risk analysis are created, developers will take some of these issue into account during system design

In general, the applications of BBNs for risk analysis are few in number. Two likely reasons for this scarceness are immediately apparent: (1) BBNs are technically more challenging to develop than KBSs and (2) user-friendly commercial software has only recently become available to help risk analysts create BBNs (<http://bayes.stat.washington.edu/almond/belief.html>), whereas comparable ANN and KBS software has been around for many years. The presentation of BBNs in an ecosystem management context by Olson (1990) is a strong argument for more extensive use of this technology. The integration of a probability model (combining both subjective judgement and available data) with a causal network representation in BBNs makes them very appropriate for risk analysis tasks.

Disturbances in forests are, by definition, changes to the status quo. In doing so, they penalize human populations, that rely on constancy for survival. While forest ecosystem

disturbances are a certainty, exactly when and where they occur and how severe their effects are uncertain events. This generates risk. Unfortunately, there is much we do not know about what causes disturbances and how they will impact forest resources. In most cases, neither do we have good data to make predictions. The AI techniques covered here offer some useful tools for dealing with uncertain/missing knowledge and data. In many cases, these methods can augment more traditional approaches and, in other cases, can replace previous methods due to their improved predictions, ease of use, or theoretical advantages.

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# Risk Analysis in Forest Management

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