ADAPTIVE FIRE POLICY

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Abstract-Adaptive resource management is a continuous learning process in which current knowledge always leads to further experimentation and discovery. Adaptive management evolves by learning from mistakes. Designing adaptive management strategies involves four tasks. First, the problem must be defined and bounded. There is growing recognition of the need to define and bound problems at the landscape level. Second, existing knowledge must be readily accessible so that errors can be detected and used as a basis for further learning. The current information structure supporting fire management was designed to support the 10 a.m. policy and is inadequate to support current policy. Expert systems and other recent developments in artificial intelligence can provide the necessary means to develop an accessible repository of current knowledge. Third, the inherent uncertainty and risk surrounding possible future outcomes must be displayed.- Bayesian decision analysis can be used to deal with uncertainty and risk. Fourth, balanced policies must be designed. These must provide for resource production and protection while creating opportunities to develop better understanding. Signal detection theory and receiver operating characteristic curve analysis provide tools to help design balanced policy. These concepts are illustrated by applying them to the problems surrounding wilderness fire management and the need for long-range tire danger information.

INTRODUCTION - SEEKING A BALANCE

The need to balance competing and often conflicting objectives is a problem whenever policy is being made. In resource management, there is often the need to balance utilization with preservation. The disputes about wilderness designation and forestry activities in spotted owl and red-cockaded woodpecker habitats are controversies in search of a balance point. Several aspects of fire management require a balance. In wilderness fire management, the role of fire in perpetuating disturbance regimes in near-natural landscapes must be balanced with the necessity of protecting resources that would be damaged by fire. In smoke management the use of prescribed fire must be balanced with minimizing the nuisance of smoke. During periods of high fire danger, shutting down the woods to protect them must be balanced with the need to keep the woods open for people who earn their livelihood there. At the interface between wildland and urban areas, it is necessary to balance the threat of wildfire and the costs of risk-reduction measures. How should government regulatory agencies go about determining the balance point? And how can they describe their search for balance and its results to affected parties?

ADAPTIVE RESOURCE MANAGEMENT

Adnptivc resource management (Clark 1989, Holling 1978, Saveland 1989, Thomas and others 1990, Walters 1986) recognizes the fact that the knowledge we base our decisions on is forever incomplete and almost always shrouded in uncertainty. Management is a continual learning process that evolves by learning from mistakes. Several authors have expressed the importance of learning from failure. "You have to accelerate the failure rate to accelerate the success rate" (Peters 1987). "Intelligent needs to be tolerated.

Multitudes of bad ideas need to be floated and freely discussed, in order to harvest a single good one" (Toffler 1990). "The willingness to risk failure is an essential component of most successful initiatives. The unwillingness to face the risks of failure--or an excessive zeal to avoid all risks--is, in the end, an acceptance of mediocrity and an abdication of leadership" (Shapiro 1990).

Designing adaptive policy involves four tasks. First, the management problems must be defined and bounded, often in terms of objectives and constraints. There is an increasing awareness of the need to define resource problems from a landscape perspective (Forman and Godron 1986, Naveh and Lieberman 1984). With the proliferation of geographic information systems, the importance of defining and bounding problems at the landscape level will become even more apparent.

Second, existing knowledge must be readily accessible so that errors can be detected and used as a basis for further learning. Walters (1986) used models to represent existing knowledge. The field of artificial intelligence, especially knowledge-based systems, provide additional capability to capture knowledge (Saveland 1990).

Current fire information systems are inadequate. Most, if not all, fire information systems were designed to support the 10 a.m. policy and do not adequately deal with the complexities of modem fire management. Fire occurrence reports track the efficiency of the suppression effort. When policy was changed to allow prescribed natural fires, only half of the fire *occurrence report* form *for* the Forest Service had to be filled

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out for these fires. These reports provide almost no useful historical information for managing wilderness and park tire management programs. In addition, adequate cost data is severely lacking, preventing useful economic analysis. Structure and site characteristics in the wildland urban interface are not recorded, preventing analysis of structure losses. The national weather data library is known for its missing and questionable data. Currently, there are no links between national fire occurrence databases and fire weather databases. Entrepreneurial fire managers have been able to download the data into relational databases to conduct analysis. In addition, there are plans to convert the national databases into a relational form. Forest Service fire occurrence data resides in Fort Collins while Park Service data resides in Boise in different formats, further complicating the sharing of data and historical analysis. Prescribed bum plans exist in paper copy or as a word processing document on a computer, the vast historical information largely inaccessible, tucked away in personal file cabinets. The collapse of wilderness and park fire management during the summer of 1988 was not so much a failure of policy as a reflection of an outdated information system's inadequacy to support fire management decisions in today's complex world. Information needs analysis have been conducted recently and the situation is rapidly changing for the better. In addition the coming explosion of GIS technology, with the shortage of spatial data, will improve the situation dramatically.

Third, uncertainty and its propagation through time in relation to management actions must be addressed. Fire managers all too often live in a fairytale world of deterministic models that ignore uncertainty. Bayesian decision analysis offers one means of coming to terms with the inherent uncertainty and risk.

Fourth, balanced policies must be designed. These must provide for continuing resource production and protection while simultaneously probing for more knowledge and untested opportunity. Signal detection theory provides one mechanism to help design balanced policies.

WILDERNESS FIRE MANAGEMENT - AN EXAMPLE

Signal detection theory (Egan 1975, Saveland and Neuenschwander 1990, Swets and Pickett 1982, Wilson 1987) divides a decision problem into three parts: state of nature, response, and outcome (fig. 1). State of nature refers to presence or absence of a signal at the time a person makes a response. The signal is either present or absent. Responses are alternative actions decision makers must choose between. Decision makers can control their response, but have no control over the state of nature. They can respond by saying that they detect signals or that they do not. The point where a person switches between responding yes and responding no is the threshold of evidence. If the signal strength is greater than the threshold of evidence, the response is yes. If signal strength does not reach the threshold of evidence, decision makers will not detect the signal and the response will be no. The threshold of evidence can be varied. As the threshold of evidence is increased, a person is more likely to say no, thus reducing the number of false alarms, but increasing the number of misses. As the threshold of evidence is decreased, a person is more likely to say yes, thus reducing the number of misses and increasing the number of false alarms. This inherent trade-off between misses and false alarms provides the opportunity to find a balance point. A response combined with a state of nature results in an outcome for which the decision maker has some level of utility. One of the strengths of decision theory is that it separates the decision from the outcome.

Response	State of Nature: Signal Present s	State of Nature: Noise n
Yes Y	HIT $P(Y \mid s)$	FALSE ALARM $P(Y \mid n)$
No N	MISS $P(N \mid s)$	CORRECT REJECTION $P(N \mid n)$

Figure 1 .-The signal detection paradigm.

Response	State of Nature: Undesirable Fire	State of Nature: Desirable Fire
Initial Attack	HIT	FALSE ALARM (????)
Do not Initial Attack	MISS (Yellowstone '88)	CORRECT REJECTION

Figure 2.--Signal detection for wilderness fire.

The wilderness fire decision can be divided into two responses that combine with two states of nature to produce four possible outcomes (fig. 2). The decision maker could choose to suppress a tire that, had it been allowed to bum, would have eventually exceeded acceptable conditions (i.e. become a wildfire). This hit is a desirable outcome because money has been saved by putting the fire out when it was small. Second, the decision maker could choose to let such a fire bum, in which case it would have to be put out later. This miss is an undesirable outcome because the costs of putting out a fire increase exponentially as the fire's size increases.

Third, the decision maker could choose to put out a firc that, had it been allowed to bum, would not have exceeded acceptable conditions (i.e. would have stayed within prescription). This false alarm is an undesirable outcome bccause an opportunity to allow fire to play its natural role has been missed. Fuel management benefits are not realized, firefighters are exposed to unnecessary risk of injury, and unnecessary costs associated with the suppression effort are incurrcd. Perhaps most important, nothing is learned. There is no increase in knowledge. Although this block and the hit block can be discussed conceptually, they are counterfactuals, and there is no way to determine these blocks in reality.

Finally, the decision maker might choose to let a fire bum, and this fire would stay within prescription. This correct rejection is another desirable outcome. Fire is allowed to play its natural role in maintaining various ecosystems, benefits associated with fuel management are realized, and the costs of fire suppression are saved.

Thus, the strategy for wilderness fire management is to allow as many non-problem-causing fires to bum as possible. For fires that are expected to cause problems, quick suppression while the fire is small is necessary to minimize costs and damages.

Long-range assessments of fire danger are key factors when managers have to decide whether to suppress specific wilderness fires. The fire danger prediction task can also be put into a signal detection framework (fig. 3). When

Response	State of Nature: High Danger	State of Nature: Low Danger
Predict High	HIT	FALSE ALARM
Predict Low	MISS	CORRECT REJECTION

Figure 3.--Signal detection for long-range forecasting.

lightning ignites fires early in the season, there must be an assessment of what fire danger conditions are likely to evolve later in the season.

An analytical procedure called the receiver operating characteristic (ROC) curve is an inherent part of signal detection theory. The ROC curve is a plot of the percentage of hits on the Y axis against the percentage of false alarms on the X axis (fig. 4). An ROC curve summarizes the set of 2 x 2 matrices (fig. 3) that result when the threshold of evidence is varied continuously, from its largest possible value down to its smallest possible value. The upper left-hand comer, where the percentage of hits equals one and the percentage of false alarms equals zero, represents perfect performance. The positive diagonal, where the percentage of hits equals the percentage of false alarms, is what would be expected based on pure chance.

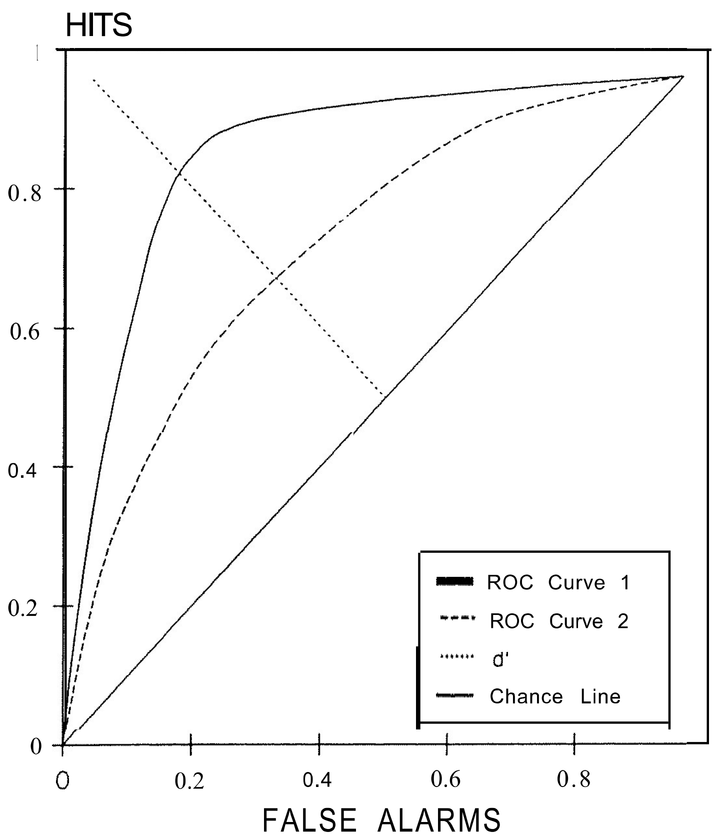
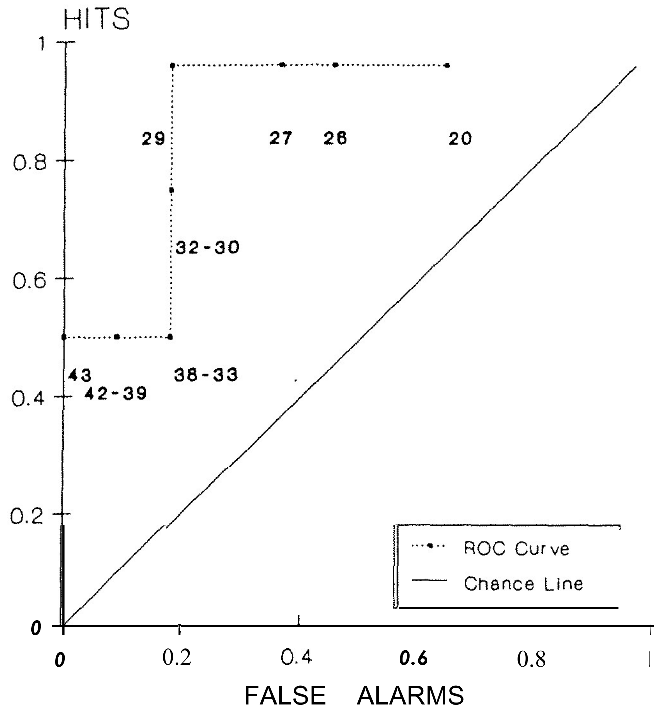


Figure 4.--Receiver operating characteristic (ROC) curves.

Various strategies can be used to select an appropriate threshold of evidence. One such strategy, minimax, attempts to minimize false alarms while maximizing hits.

The ROC curve has four important properties which correspond to the four tasks required to implement adaptive resource management. First, ROC analysis requires that the problem be defined explicitly. In this case, it is necessary to say just what constitutes high fire danger and what does not. In the example to follow, fire danger is defined in terms of the energy release component (ERC) of the national fire danger rating system. If the ERC at a certain date early in the fire season exceeds a threshold (predict high fire danger) and the ERC exceeds a critical value later in the fire season (late-season fire danger is high), the result is a hit. If the ERC early in the fire season exceeds a threshold but the ERC does not exceed the critical value later on, the result is a false alarm. Miss and correct rejection can be defined in a similar manner. The threshold varies to display the possible trade-offs. The critical value is site specific. The manager can select a critical value based on past experience. For example, noting that tires start to spread rapidly on north slopes, develop into crown tires, and become uncontrollable at a certain value, would be a suitable critical value. An explicit definition of fire danger and fire severity will enhance communication between fire staff and line officer decision makers, and between the line officer and the public. Second, the ROC curve displays skill prediction, or how much confidence to place in the prediction. A point near the chance line does not warrant much confidence, while a point close to the upper left-hand comer is reliable. The area under the curve is a measure of skill prediction and can be compared to chance. Skill prediction can also be considered a measure of our current state of knowledge. As more knowledge is obtained prediction systems should improve, and this improvement should result in new ROC curves that get progressively closer to the upper left-hand comer, which represents perfect prediction. Third, the ROC curve expresses the inherent uncertainty of the predictions in terms of Bayesian probability. Each point on the curve corresponds to percentages of hits, false alarms, misses, and correct rejections on a scale of zero to one. Fourth, the ROC curve displays the possible trade-offs between misses and false alarms as the threshold of evidence varies. A high percentage of hits is often possible only when there is a high percentage of false alarms. To reduce the number of false alarms often implies an increase in the number of misses. Selecting an operating point on the ROC curve is selecting a balance point.

Figure 5 is an ROC curve developed for the Westfork Ranger District weather station. The Westfork weather station collects data used by those who make decisions about prescribed natural fires in a portion of the Selway-Bitterroot Wilderness. Fire danger prediction is explicitly defined by a threshold ERC early in the fire season and a critical ERC later on in the season. A critical ERC value of 52 was chosen. During the period from 1973 to 1987, the ERC reached 52 in four of the fifteen years (1973, 1977, 1978, and 1979). Thus in 73 percent of the years, the ERC does not exceed 52 (low danger years), while 27 percent of the years, the ERC exceeds 52 (high danger years). The ROC curve displays percentages of hits and false alarms for threshold ERC values from 20 to 43. The probability that the ERC exceeds 29 on July 10 given that the ERC exceeds the critical



1988 ERC 41
Critical ERC = 52
Data: 1973-1987

Figure 5.--Long-range ERC forecast for Westfork R.D. on July 10.

value of52 later on in the fire season (hit) is 1.0. The probability that the ERC exceeds 29 on July 10 given that the ERC does not exceed the critical value of 52 later on in the tire season (false alarm) is 0.18. it follows that the probability of a miss at that point on the ROC curve is 0 and the probability of a correct rejection .82. Skill prediction is high. The area under the ROC curve is 0.91. If it were important to minimize the number of false alarms, the threshold of evidence could be increased to 43. This would reduce the number of false alarms by 18 percent, but would increase the number of misses by 50 percent. Saveland (1989) presents a similar analysis for Yellowstone National Park.

CONCLUSIONS

Most resource management controversies require seeking a balance between competing, conflicting objectives. Finding a balance is an integral part of adaptive resource management. Implementing adaptive policy involves four steps: defining and bounding the problem, representing current knowledge, representing the uncertainty surrounding our predictions of the future, and designing balanced policies that provide for resource production and protection while permitting experimentation aimed at increasing knowledge. Receiver operating characteristic curve analysis can assist adaptive resource management. ROC forces explicit definitions, represents current knowledge through skill prediction and readily displays uncertainty and possible tradeoffs.

Adaptive resource management points out the limits of our current knowledge and the importance of increasing our knowledge of the structure and function of natural resources. In fact, knowledge can be considered a resource. Surely our policies should promote the acquisition of *new knowledge.*

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