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Wildland Fire Prevention: Today, Intuition--Tomorrow, Management[1]

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Abstract: Describes, from a historical perspective, methods used to characterize fire prevention problems and evaluate prevention programs and discusses past research efforts to bolster these analytical and management efforts. Highlights research on the sociological perspectives of the wildfire problem and on quantitative fire occurrence prediction and program evaluation systems. Focuses on current and future advances in fire prevention management due to research in four critical areas: modeling fire occurrence, measuring prevention effectiveness, measuring economic efficiency, and optimizing program mix.

YESTERDAY

Over the years, fire managers and researchers have developed a number of methods to characterize fire prevention problems and evaluate prevention programs. Perhaps their efforts began as far back as 1905 when, on the first Forest Service fire report form, field personnel documented the fire cause in addition to 14 other items of information (Donoghue 1982). Fire causes were, and continue to be, key elements in the development and analysis of fire prevention programs. First devised to pinpoint how fires started, fire-cause categories were later expanded to include persons responsible for wildfire ignitions.

These data, combined with other fire report information and summarized in tables and on charts and maps, have been used for decades to develop fire occurrence histories. Based on this information, for example, fire managers in North America know the temporal distribution of wildfires by the month, week, day, or hour (Haines and others 1975; Simard and others 1979). The major problem is that temporal fire occurrence distributions average many individual occurrence patterns, most of which are decidedly not average. Knowing what happened yesterday or last year provides little information about tomorrow or next year. Likewise, the same data disclose <u>where</u> fires occur, from a strategic scale (Simard 1975) to a management scale (Haines and others 1978) to a local scale (Meyer 1986). These data also indicate the types of fuels in which these fires burn (Haines and others 1975).

Although spatial and fire cause distributions are not constant over time, they are relatively conservative (particularly compared to weather) and, unlike temporal data, can provide many insights into the near future. From fire report data and consequent analyses, managers have been able to characterize their fire prevention problems, determine the actions needed to solve them, and allocate resources to implement their prevention programs.

These analytical and management efforts have been bolstered by research that developed along

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two parallel tracks--one dealing with sociological perspectives of the wildfire problem and the other with quantitative fire-occurrence prediction and program evaluation systems. A major thrust of the sociological research over the years has been to develop demographic profiles of select subpopulations that differ significantly from the general public. The attitudes and characteristics of these groups (such as arsonists, hunters, children, and rural residents), their knowledge of fire, and/or their reasons for setting fires have been documented in numerous reports spanning four decades of research (e.g., Shea 1940; Kerr 1958; Folkman 1963; Siegelman and Folkman 1971; Bertrand and Baird 1975). One of the underlying objectives of this research was to supply managers with useful information about high-risk groups likely to start wildfires through carelessness, ignorance, or arson, thus providing a basis for developing effective fire prevention programs.

To a lesser extent, researchers also studied the attributes of fire prevention message sources as well as the characteristics and uses of prevention messages and channels of dissemination. Informal sources of fire prevention messages such as personal contactors and local opinion leaders in the rural South were characterized by several researchers (e.g., Dickerson and Bertrand 1969; Doolittle and others 1975; Doolittle 1979). The mass media, including television, radio, newspapers, signs, and billboards, were also recognized as primary sources of prevention information. Scientists studied how and when these media were used, their content, their ability to change attitudes, and their impact on message retention (e.g., Griessman and Bertrand 1967; Bernardi 1970; Doolittle and others 1976; Folkman 1973). By examining the sociological perspectives of the wildfire problem, these scientists have developed a fund of knowledge critical to designing effective fire prevention programs.

Other scientists have tried to develop fire occurrence forecasting and program evaluation systems that go beyond descriptive statistics and analyses. Nickey and Chapman (1979), for example, developed a probability model to evaluate the Red Flag Alert Program applied during periods of Santa Ana winds in Southern California. From estimates of the probability of human-caused fire occurrence and the conditional probability of fire size at suppression, they determined the expected suppression costs for a patrol area for any given day. By comparing expected suppression costs to actual costs, they calculated the Expected Monetary Value (EMV) or the "estimated gain" of added prevention efforts. There are no statistics, however, on the accuracy of their method when applied to localized areas on a daily basis.

Attacking the problem from a different perspective, Nickey (1980) described a method to quantitatively analyze fire occurrence using c control charts. This graphic method is used to determine whether changes in fire occurrence are due to chance or to changes in external factors such as weather or population. The method is founded on the Poisson distribution which provides a model of the expected number of wildfires within a given week. According to Nickey, control charts provide a way to quantitatively evaluate increasing or decreasing fire occurrence patterns over time, to forecast expected future fire occurrence under stable external conditions, to determine the effects of unusual weather conditions, and to evaluate the performance of fire prevention programs.

To "provide a definitional and conceptual framework for putting wildfire prevention management on a badly-needed logical foundation," J. M. Heineke and S. Weissenberger (1974) developed a stochastic model of human-caused ignitions that, together with their model for fire damages and decision costs, could be used to determine prevention decisions that minimize the expected value of fire prevention costs plus fire losses.

As Wetherill (1982) states so pointedly, however, despite all these research efforts and "the easily recognized benefits of program evaluation. . .logical, documented evaluation of the fire prevention programs of forestry agencies is seldom done. . .Prevention personnel are aware of the lack of evaluation methods, but are unsure how to go about evaluating a program without the sole reliance on fire occurrence statistics." Furthermore, he notes, "Fire occurrence alone is an inadequate indicator of prevention program value even though it is the most commonly used indicator. The vast judgmental gap between prevention activities and the benefits of those activities cannot be bridged by intuition alone. Why must forest fire prevention be unscientific when the rest of our forestry practices are governed by scientific principles? Evaluation is the key to unlocking this understanding." It is this alone that will take us from an era characterized by intuitive judgments and ad hoc decisionmaking into one of sound management shored by a strong foundation built on scientific principles and practices.

TODAY

The foundation of prevention management will be laid on four sequentially related cornerstones necessary for fire prevention program evaluation:

- modeling fire occurrence
- measuring prevention effectiveness
- measuring economic efficiency
- optimizing program mix.

In the 1980's, research has begun to tackle each of the above and early results are just beginning to emerge.

Modeling Fire Occurrence

The primary cause of the great temporal variability in fire occurrence is weather. It follows, therefore, that we must understand weather effects on fire occurrence--from daily prediction to annual normalization.

Weather Influences

Daily fire occurrence prediction and seasonal normalization can be tied to most fire-danger rating systems. For example, Lynham and Martell (1985) explained 47 percent of the variability of annual resident-caused fires in five regions of Ontario by using a daily prediction model (based on the Canadian Fine Fuel Moisture Code) and integrating the daily predictions over a season. Haines and others (1983) developed a similar model, using the Model G Ignition Component (IC-G) of the U.S. National Fire-Danger Rating System (NFDRS) (fig. 1). When integrated over a year, using seven Northeastern weather stations (each representing an area of 6,170 square kilometers), this model similarly explained 46 percent of the average annual variation in fire occurrence.

As the length of the integration period decreases, however, the amount of variability explained by simple predictors decreases markedly (fig. 2). In other words, the shorter the integration period, the more difficult the

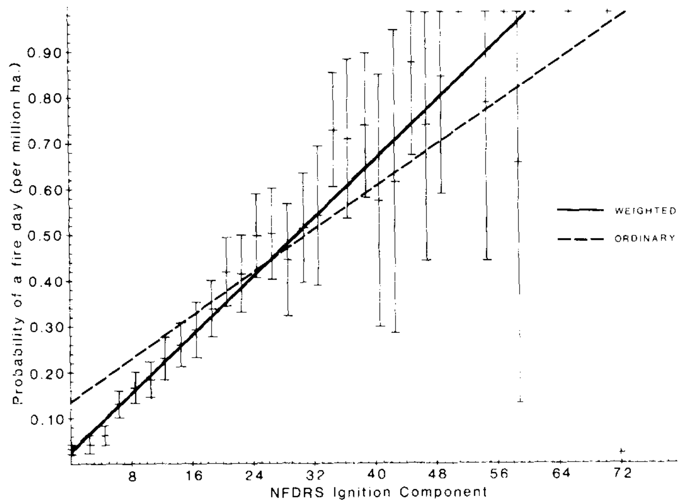

Figure 1--Probability of a fire day (per million hectares) vs. the NFDRS IC-G for grouped data. Horizontal bars represent the mid-point and 95 percent confidence limits for each group (Haines and others 1983).

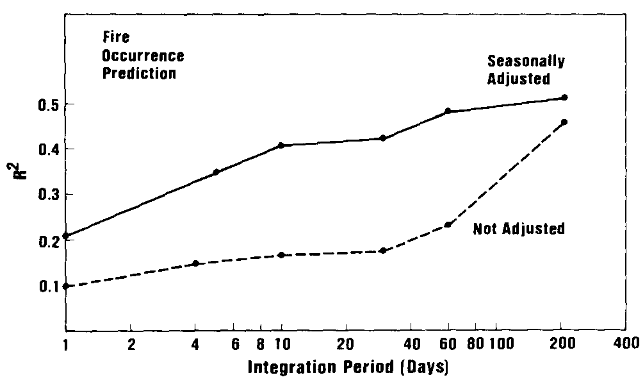

Figure 2--Percent of fire occurrence variability explained vs. length of integration period.

prediction. Specifically, only 10 percent of daily fire occurrence variability in the Northeastern U.S. is explained by IC-G. Although nonweather-related stochastic elements presumably play an increasingly important role at shorter time intervals (and for smaller areas), weather effects are also more complex. For example, failure to incorporate the bimodal eastern fire season significantly impacts daily fire-occurrence prediction. To overcome this deficiency, Lynham and Martell (1985) stratified the fire season into five sub-seasons. More recently, Martell added trigonometric regression to a logistic occurrence model to accomplish this purpose.[3] As part of a separate study, we normalized monthly occurrence per 100 units of IC-E (fig. 3) and adjusted the daily occurrence prediction model of Haines and others (1983) (fig. 2). This simple improvement doubled the explained daily variability to 21 percent. A more fundamental approach to fire seasons would be to model the controlling plant phenology process directly.

Kourtz (1984) employs a stochastic fire occurrence model developed by Cunningham and Martel (1973f). Five classes of the Canadian Fine Fuel Moisture Code, two seasons, and a historical data base are used to predict expected daily fire occurrence (Ward 1985). Occurrence probabilities (in thousandths of fires) are calculated for 20 x 30 kilometer grid cells (to coincide with standard base maps). The system employs "Bayesian analysis" of the historical data base. Essentially, for each day that observed fire occurrence departs from the historical trend, occurrence probabilities are gradually shifted upwards or downwards accordingly, thus giving greater weight to the most recent data. Such an analysis could be run annually or even monthly or weekly to monitor short-term changes in human-caused fire occurrence patterns. Statistical analysis of the original model indicates that it is a good predictor of annual fire occurrence over an 11,000 square kilometer district (Cunningham and Martell 1973); no data are available on daily accuracy within a 600 square kilometer cell.

When integrated over a year, most fire occurrence predictors are highly intercorrelated. High annual average values for a long-term component are normally associated with high average short-term component values. This is much less so for daily prediction, however. For example, adding a long-term (Palmer Z-Index) threshold to an NFDRS IC-O threshold provides a background signal that yields notable improvement in the discrimination power of a daily Extreme Fire Potential Index (fig. 4) (Simard and others 1987a). An ideal

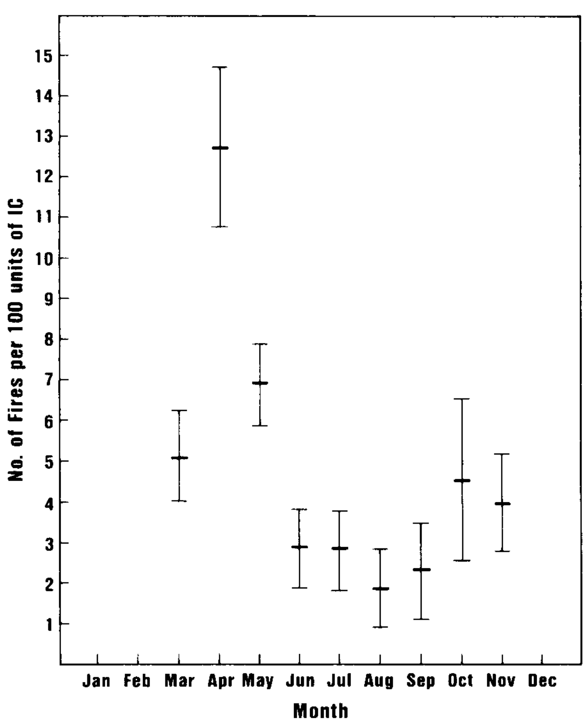

Figure 3--Monthly fire occurrence probability per 100 units of NFDRS IC-E.

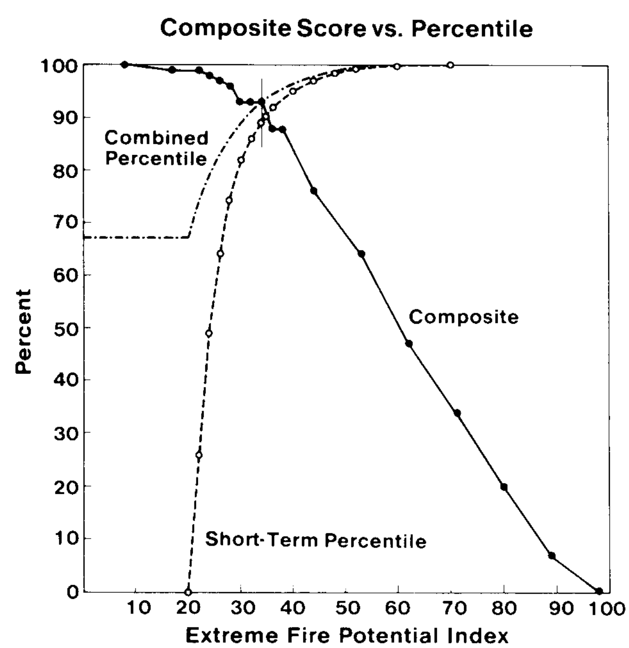

Figure 4--Percent of U.S. extreme fires identified (composite score) vs. Extreme Fire Potential Index (EFPI); percent of Northeastern U.S. days below EFPI threshold vs. EFPI (Simard and others 1987a).

[3]Unpublished data on file, University of Toronto; Forestry Faculty; Toronto, Ontario, Canada.

weather-driven daily fire occurrence model would incorporate short-, medium-, and long-term components as well as phenological and other seasonal adjustments.

There is also a class of global weather variables that show some promise for seasonal fire occurrence prediction in some regions. For example, by January 1, global meteorologists are able to predict the occurrence and strength of an El Niño during the coming year with some skill. Adding the January 1 state of the Quasi-Biennial Oscillation of the upper stratospheric zonal winds permits us to predict half of the variability of fire activity for the coming fire season in six Southern States (Simard and others 1987b).

Examined individually, these daily and seasonal fire occurrence prediction models are disjointed and fragmentary. They tend to be related to specific areas and are data-dependent. When seen as a whole, however, a pattern of increasing knowledge can be discerned. We are beginning to understand individual components of the weather-fire occurrence process and to aggregate individual results. Generally applicable weather-related daily fire occurrence prediction and seasonal weather normalization will surely be a reality before the year 2000.

<u>Other Influences</u>

In examining relationships between human-caused fires in the Eastern U.S. and nonprevention influences, Donoghue and Main (1985) found a strong latitude effect (fig. 5).

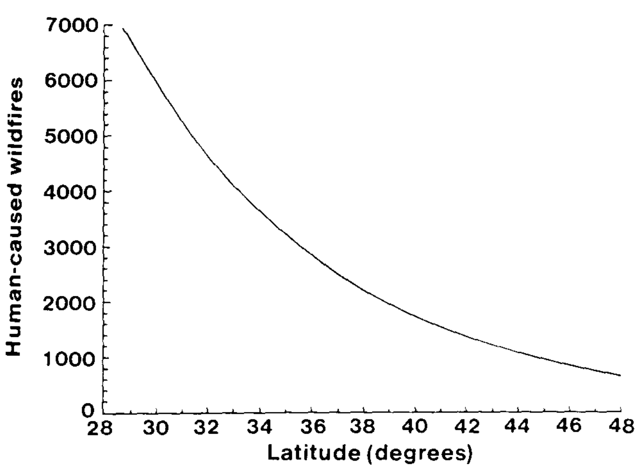

Figure 5--Number of human-caused wildfires in the Eastern U.S. vs. latitude (Donoghue and Main 1985).

In essence, as latitude increased from south to north, fire occurrence decreased. Latitude integrates several factors that can influence fire occurrence such as length of fire season, fuel types, and cultural attitudes towards fire. For example, because Southern States have longer fire seasons, there are more opportunities for fires to occur. As a corollary, the effect of a unit of prevention effort is diluted over a longer period, and should, therefore, have less impact on total fire occurrence. To test the former hypothesis, we normalized fire seasons for 27 Eastern National Forests by dividing fire activity[4] for each week by the highest weekly activity. We then defined the seasons as 10, 15, 20, and 25 percent of maximum activity but found that the results are independent of how the seasons are defined. Our investigation showed that latitude alone explains half of the variability in length of fire season in the Eastern U.S. (fig. 6).[5] Further investigations should yield additional measurable processes that can be used to more directly link latitude and fire occurrence.

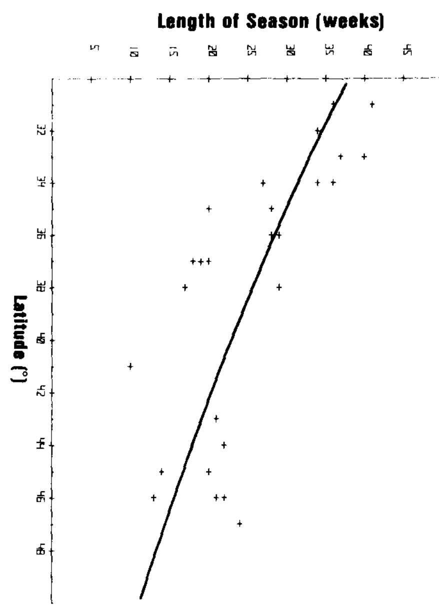

Figure 6--Number of weeks with fire activity greater than 10 percent of peak weekly activity vs. latitude.

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[4]Each Class A fire received 1 point, Class B=2, C=4, D=8, E=16, F=32 points.

[5]Unpublished data on file, North Central Forest Experiment Station, East Lansing, Michigan.

Donoghue and Main (1985) also found a weak (R^2 =0.08) but statistically significant ($P<0.001$) parabolic relation between average state nonmetropolitan population density and human-caused wildfires in the Eastern U.S. (fig. 7). At one end of the scale, the relative fraction of wildland has decreased sufficiently to reduce the risk that an ignition source will start a wildfire. At the other end, there are fewer people (hence, potential ignition sources)--again resulting in fewer wildland fires. Lynham and Martell (1985) found a similar relation for resident-caused fires in Ontario. We suspect that other demographic variables or attributes of the local economy, such as median income, unemployment rate, or types of industry, might also have merit in quantifying resident-caused wildland fires.

As with the weather component of fire occurrence, these are early, incomplete results. The methods show promise, however, that in the future we will be able to compensate for many of the nonprevention influences on fire occurrence. Eliminating such background "noise" will permit much more accurate measurements of prevention program effectiveness than are currently possible.

Measuring Prevention Effectiveness

Pottharst and Mar (1981) studied the effectiveness of engineering improvements in reducing railroad fires in the Pacific Northwest. After normalizing annual railroad fire occurrence for weather differences, they measured two attributes of prevention effectiveness--total impact and implementation rate. In 1969, the State of Washington mandated installation of spark arrestors on locomotives by April 1970. Results (fig. 8) indicated that within 2 years, exhaust fires were reduced by 95 percent. The State also required installation of improved braking systems in the early 1970's. The gradual decline in brake shoe fires (fig. 8) was attributed to a gradual replacement program. Overall, this modification reduced brake shoe fires by about 85 percent. Even with engineered improvements, however, fires cannot be completely eliminated. Malfunctions and maintenance (or lack of) can notably affect system efficacy. Pottharst and Mar (1981) found a similar overall effectiveness and decline rate for Oregon brake shoe fires, but exhaust fires were reduced much more gradually than those in Washington. This was attributed to Oregon's persuasive strategy vs. Washington's legal requirement. It is clear that, when cause-and-effect are directly linked and adequate data with minimal "noise" are gathered, a classic intervention study can reliably measure prevention effectiveness.

Outside the engineering field, cause-and-effect relationships are much more tenuous; many are unknown. The noise level in the data increases markedly. In such cases, a cross-sectional analysis is often more productive. Donoghue and Main (1985) used such an approach to examine the effectiveness of law enforcement in preventing arson fires. They

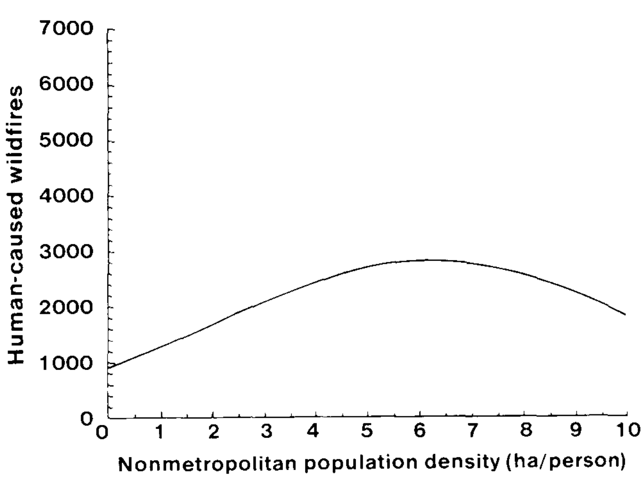

Figure 7--Number of human-caused wildfires in the Eastern U.S. vs. nonmetropolitan population density (Donoghue and Main 1985).

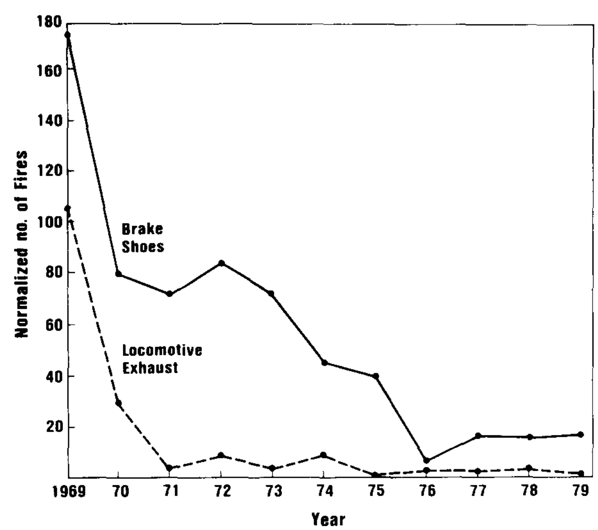

Figure 8--Number of railroad fires in Washington by year (data from Pottharst and Mar 1981).

collected data on the number of fire-related prosecutions, convictions, and settlements in 27 Eastern States during 1972-1981. They partially normalized fire occurrence based on latitude, monthly precipitation departures from normal, and nonmetropolitan population density.

They found that, although enforcement was not significantly related to all fires, it was significantly related to arson fires (fig. 9). Although the relation is weak ($R^2 = 0.04$), the breadth of the data base, general consistency of results within individual States, and conformance with what would be expected lend credibility. At low enforcement levels, small changes yield large decreases in the number of arson fires. At higher levels, marginal productivity is notably less. Going from no law enforcement to a high level of enforcement reduces arson fire occurrence by about half (compared to an average of 90 percent for engineering improvements and railroad fires). Although only an exploratory study, these results indicate that it is possible to quantitatively link a sociological prevention activity to wildland fire occurrence, even though many of the causative pathways between them are ill-defined.

Measuring Economic Efficiency

Simply counting numbers of fires presents an incomplete evaluation of prevention programs. Ultimately, the cost of preventing fires must be compared with the savings of the fires that did not occur. Recently, Donoghue and others. (1987) adapted a four-quadrant fire economic model (Simard 1976) to fire prevention. They used a case study employing enforcement and arson fire data from Arkansas to demonstrate how the model could be applied. The model incorporates four functions (fig. 10). Quadrant I contains a loss function, defined by the relation between the number of fires and suppression cost plus net value change (CS + NVC). Quadrant II contains the previously described enforcement production function or the relation between units of enforcement and number of arson wildfires. Quadrant III contains the enforcement cost function or the relation between costs and units of enforcement. Quadrant IV contains a cost transform--in other words, a line that simply equates the two cost axes. Graphically, the nomogram facilitates transforming the enforcement cost function in Quadrant III to Quadrant I. Summing the two functions in Quadrant I yields the traditional least cost plus loss presentation (fig. 10).

Lacking detailed information, an average CS + NVC per fire was used in Quadrant I. An average cost per unit of enforcement was similarly used in Quadrant III. The enforcement production function for the Eastern States was

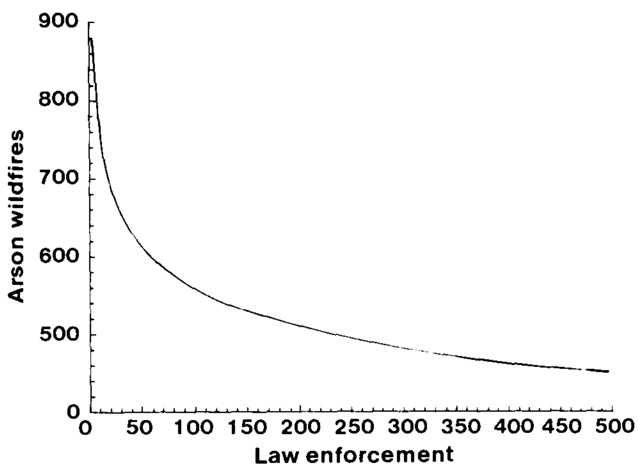

Figure 9--Number of arson fires per State vs. level of law enforcement (sum of prosecutions + convictions + settlements) in the Eastern U.S. (Donoghue and Main 1985).

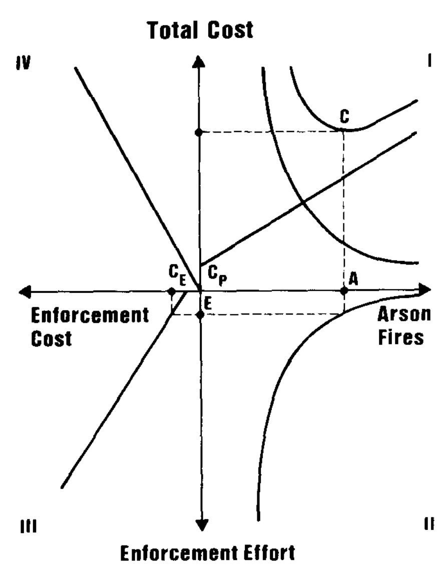

Figure 10--Four-quadrant economic model of fire prevention (Donoghue and others 1987).

mathematically calibrated fob Arkansas and for two regions within the State[6]

Individual solutions were calculated for these two regions (fig. 11). As expected, the efficient solution involves substantially more enforcement expenditures in higher value loblolly-shortleaf pine than in lower value oak-hickory areas. Sensitivity analyses of enforcement costs disclosed that substantial expenditures were justified in the loblolly-shortleaf type across a wide cost range. In contrast, increasing enforcement costs in the oak-hickory type resulted in notable reductions in the efficient level of expenditures.

We extended the model of Donoghue and others (1987) to derive a mathematical solution to the problem. (Even a simple sensitivity analysis

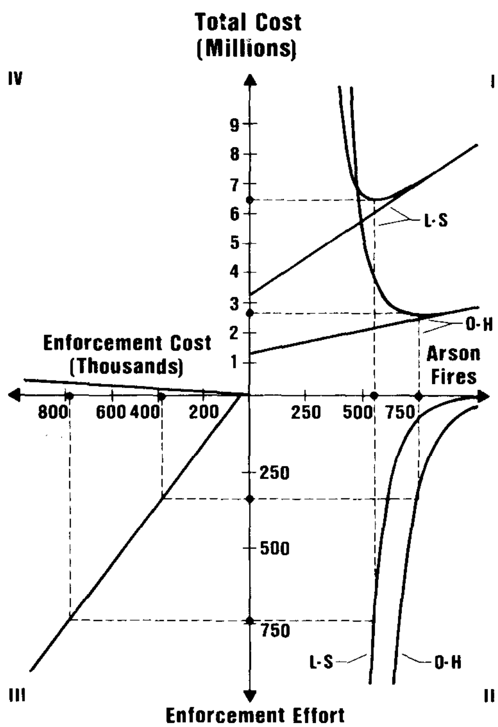

Figure 11--Optimum law enforcement levels in loblolly-shortleaf and oak-hickory forests in Arkansas (Donoghue and others 1987).

[6]Eastern States values of A_0 and a more detailed description of methods for calculating within-state values can be found in an unpublished report on file, North Central Experiment Station, East Lansing, Michigan.

quickly becomes cumbersome with a four-quadrant model.) We started with the production function (Donoghue and Main 1985):

$$A = A_0 (E)^{-p} \quad E \geq 1 \qquad (1)$$

where: A = no. of arson fires

A_0 = no. of arson fires with no enforcement

E = units of enforcement (prosecutions + convictions + settlements)

p = productivity coefficient (-0.134)

We also used the total cost function from Quadrant I:

$$C = Cf\ (A) + Ce\ (E) + Cp \qquad (2)$$

where: C = total cost

Cf = suppression cost per fire + net value change per fire

Ce = enforcement cost per unit

Cp = presuppression cost

Equation (2) assumes that the costs per fire and per unit of enforcement are constant. Although not strictly true, conceptually we can only prevent the average fire, and economies of scale are not a major factor in enforcement. These considerably lessen the significance of this assumption and simplify the mathematics. Although we bypass the mathematical development here, it is straightforward. Substitute (1) into (2), take the first derivative of C, set it to 0 (the point of minimum total cost), and solve for E:

$$E = \left(\frac{A_o pCf}{Ce} \right)^{\left(\frac{1}{p+1} \right)} \qquad (3)$$

Note that one need not know the presuppression cost (Cp) to find the efficient solution.

A value of A_0 can be calculated for each State or management area to be analyzed (Donoghue and others 1987)[6]. The Eastern value of p is fixed at -0.134 (unless examining the sensitivity of a solution to the error inherent in the production function). Assuming that the average cost per fire (Cf) and cost per unit of enforcement (Ce) are known, equation (3) yields the economically efficient number of enforcement units for the management area being analyzed. Equation (1) yields the expected number of arson fires, equation (2) yields total system cost, and each part of equation (2) yields the cost of each component of the system.

By rearranging terms into two ratios (A/E and Cf/Ce), we can present the locus of all economically efficient solutions on a single two-dimensional graph (fig. 11). In the process, the number of fires without enforcement (A_0) conveniently drops out of the solution. In addition, by using the 2-standard deviation limits of the productivity coefficient, we also show the 95 percent confidence band for the result. Put another way, this region delineates the relative fuzziness of the answer (presumably computer-calculated to a precision of four decimal places).

These results provide a glimpse into the future, when economic analyses of fire prevention (and by extension, of fire management) will be the norm. Armed with a calculator and equations 1, 2, and 3 or with figure 11 and a ruler, one can generate sets of efficient solutions so that the sensitivity of the results to what is and isn't known can be determined. Such information can bolster confidence in implementation when large input changes have relatively little impact on the output. Conversely, it can quantify the benefit to be derived from more precisely measuring the value of one or more inputs.

The power embodied in this process lies in eliminating intervening calculations. Once a production function (equation 1) is defined experimentally and costs are measured, all else is mathematically derived. This permits us to go directly to the desired solution and analyze it, rather than expending considerable energy crunching numbers just to obtain a single solution. Today, the technique is only available for one fire cause and one prevention activity in one part of the country. We suspect that a modicum of research could develop a production function for engineering and railroad fires. We hope that during the next decade or two, a set of productivity curves can be developed to cover most aspects of wildland fire prevention.

Optimizing Program Mix

A key part of this activity lies in using Operations Research (OR) techniques to solve prevention problems. The past two decades are rich with OR analyses of wildland fire management problems. Martell (1982) reviewed more than 200 articles on the topic. The list of analyses is long: prevention planning, fuel management, strategic and tactical detection planning, resource acquisition and strategic deployment, resource mobilization, initial attack dispatching, extended attack management, fire impact management, and training. Martell (1982) concludes, however, that "although many of the studies. . .have produced valuable insights into complex fire problems, fire managers seldom rely on the results of OR studies to guide their decisionmaking." He lists several possible causes for this applications gap, one of which is particularly germane here--"efforts to implement OR continue to be hampered by difficulties in predicting the physical and economic consequences of alternative courses of action." In essence, OR provides powerful tools for optimizing mixes of things when their relative costs, benefits, and substitutabilities are known.

In the business of preventing wildfires, we can estimate relative costs (surprisingly crudely in most cases), we know something about the benefits for just one or two cases, and virtually nothing about substitutabilities. For example, we compared law enforcement exclusively to arson fire occurrence, yet there is a weaker (statistically marginal) relation to debris burning fires. Total law enforcement effectiveness will somehow have to be prorated between these two and possibly other causes. Similarly, rural population density explained 21 percent of the variability in debris fires and 8 percent of the variability in arson fires (Donoghue and Main 1985)--again, necessitating some form of proration. There may also be an as yet unexplored relation to other causes. At one end of the substitution scale, railroad fires and related prevention activities may be sufficiently independent of other causes that they can be treated as such. At the other end of the spectrum, measuring and distributing the effectiveness of multi-media Smokey Bear campaigns among the various fire causes would seem to be a truly challenging problem. Once we understand the technical relationships between things that we do and things that we want to accomplish, there are powerful analytical tools available to help us do more of the latter and less of the former.

TOMORROW

What does the future hold for wildland fire prevention management? Before the year 2000, we expect that daily fire occurrence prediction will be as commonplace as fire-danger rating is today. Predictions will be quantitative (e.g., number of fires, probability of large fires), and they should account for half of the observed daily fire occurrence variability in management areas on the order of a few thousand square kilometers. Within the same time frame, it should also be possible to explain two-thirds to three-quarters of the interannual variation in fire occurrence. The data are at hand, efficient computer processing techniques for large data bases are available, and we have a reasonable (though incomplete) knowledge of what's going on. What remains to be done is a decade of research in which the individual bits and pieces of what we've learned are put together in one generally applicable package.

Progress on normalizing the weather component of fire occurrence will enable us to remove much of the "noise" from prevention effectiveness data. This will, in turn, open up new opportunities to measure the effectiveness of more complex, diffused, and difficult-to-quantify prevention activities. We also expect considerable progress in normalizing other nonprevention components of fire occurrence such as sociological, economic, and demographic effects. By the year 2000, or slightly beyond, our knowledge in this field could equal our knowledge of fire-danger rating today. We emphasize that it is not necessary to understand exactly how or why a prevention activity leads to fewer fires to measure program effectiveness. This is fortunate because the historical trend of progress in understanding the how and why of wildland fire prevention leads to the conclusion that we will be well beyond even the futuring horizon of this conference before substantial progress is made in this area.

As happened for enforcement and arson fires, economic evaluation will quickly follow the measurement of prevention effectiveness. Demonstrating the feasibility of such analyses also points out the need for much better information on prevention costs and net value change than are currently available. We expect that by the year 2000, many organizations will have made considerable progress in collecting and analyzing such information, and that by the year 2010, economic analyses of prevention programs will be as common as such analyses of fire management are today.

Powerful analytical techniques for program optimization are currently available, but the interrelationships and substitutabilities between prevention activities and programs are unknown and will likely remain so for the rest of this century. Although we can solve the problem, current solutions tend to be of academic interest rather than operationally useful due, in part, to questionable inputs. As economic evaluations are completed for an increasing number of prevention programs, the usefulness of program optimization will increase. Significant progress in this final area is not likely until well into the first quarter of the next century.

Quantitative prevention management could be a reality by the year 2000. All that would be needed is a significant infusion of resources. Given the relatively low profile of prevention in current research planning, however, we see some (but not substantial) progress in the next decade or so. From a "half-full glass perspective," even some progress will make quantitative prevention management a reality by the end of the first quarter of the next century. That's about half the time that it has taken us to get this far. On the other hand, who knows? The concept might just take hold with a few innovative managers. These people might then decide to drive the system rather than letting it drive them. When that starts to happen, great things are often achieved. In our opinion, prevention management is inevitable. We can make it happen sooner or let it happen later--the choice is up to us.

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