TOWARD A THEORY OF MESO-SCALE WILDFIRE MODELING:

A COMPLEX SYSTEMS APPROACH USING ARTIFICIAL NEURAL NETWORKS

by

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TOWARD A THEORY OF MESO-SCALE WILDFIRE MODELING: A COMPLEX SYSTEMS APPROACH USING ARTIFICIAL NEURAL NETWORKS

Ronald J. McCormick

Under the supervision of Professor Timothy F. H. Allen

At the University of Wisconsin - Madison

Modeling wildfire spread patterns is a complex problem involving long-term fuel accumulation (site history) with short-term thermodynamics. Two general approaches to modeling wildfire spread patterns are fine-scale mechanistic or broad-scale probabilistic. Mechanistic approaches scale locally (micro-theory) to what keeps a fire burning while fire spread in probabilistic models is constrained by the rate of percolation across the landscape (macro-theory). Changing spatial and temporal scales of fire environment variables lead to the inherent unpredictability found in middle number systems. Extant fire models lose predictive power when subtle shifts in environmental variables cause a qualitative change in fire behavior. Artificial neural networks (ANNs) are designed for problems with cross-scale relationships that produce non-linear changes in system behavior (meso-theory). Even though the system appears middle number, the ANN recasts system structure until, at an appropriate level of analysis, prediction becomes possible. The difficulty with ecological systems is they invite being cast as complex, and complex systems require different causal models. A systems approach incorporates the explanatory power of positive and negative feedbacks and the recognition of emergent system behavior. Because complex systems do not invite definitive answers, we need complex systems methodologies like ANNs to offer

prediction with good explanatory power. An ANN wildfire spread model was developed that integrates across scales of fire environment variables. Preliminary results support the proposed meso-theoretical fire environment definition and ANN-based modeling approach.

Acknowledgments

14 May 1997... I started on the path leading to that particular day and this particular dissertation in 1981, but could not have known that then. 1981 was the year I met Chris Stickland and Eunice Padley in the Upper Peninsula of Michigan. Nearly 15 years, three states and two academic degrees later I again connected with Eunice. She gave me a job that opened a number of new opportunities for me and eventually funded this research project. But it was Chris, who I ran into on a beach in Florida in 1990 and married soon after, that sat with me in the RathSkeller on 14 May 1997, a Wednesday. The byzantine process that is graduate school had led me into a feeding frenzy on that particular day, and I was ready to step off the path. Chris convinced me that I should continue, and though the process never became any less surreal I knew Chris would kick my *** if I quit. I owe so much to her that cannot be repaid.

Along with Eunice, Dave Cleland, John Wright and Eric Gustafson at the North Central Research Station were always supportive and helpful during the numerous academic crises I faced. Don Waller took a chance on me when no one else would, and supported my efforts while I searched out a research topic. He was also magnanimous enough to step aside as my advisor when our research interests diverged. So, on 25 September 1997 I was looking for another academic home. Tom Brandner, office mate and good friend, had been following my progress and told me his advisor, Timothy F.H. Allen, was interested in talking to me.

Tim and I had met many times previously and had danced around each other for years. I

thought he was all bluster and he thought I was grumpy and just a bit too pleased with myself. I had always felt that my research ideas were important and new, but within 15 minutes of explaining my project to Tim he told me WHY it was important. For that I am eternally grateful to him. He understood what I wanted to do better than I did, and our conversation that day sent me down the path I currently travel. I was converted, and became what is known around the Allen Lab as a Systems Zealot. I embraced complex systems thinking with all my soul, and cannot remember a time when I did not think in terms of catastrophe curves and Holling's figure-8.

Not satisfied with mere scholarly display, Tim required depth in understanding. His teaching method stressed the application of concepts, not the storing of facts in short-term memory to be discarded after one-time use on a test. You have to see systems in every structure and process around you before you can go out into the world and teach others. I had always felt there was something missing from standard, scientific method-based approaches to ecology, but could never quite say what. Now I have the elegant and subtle vocabulary of systems to express it. I am astounded by the things Tim inspired me to learn in three short years, and the skills I acquired along the way. Graduate school was often a bit beyond comprehension for me, but having a cup of tea and a fine lunch on Tuesday in Tim's Lab made that tolerable. I will never miss school, but I do miss Sandbox, and will return as often as I can.

My committee members, David Mladenoff, Frank Scarpace, Monica Turner, and Steve Ventura, were certainly integral to the whole process. Their incisive questioning forced me to understand what artificial neural networks modeling is all about, and led me to develop a language to express my ideas to a very diverse group.

To complete this section, it is traditional to list the persons who helped along the way. I'll do that now, in no particular order of importance, merely the order that they come to mind: Matt Bobo, Paul Pope, Tom Fitzhugh, Darcee Killpack, and John Walkey (the core members of the Permanent Floating Riot Club), Jonathan Chipman, Math Heinzel, The Puth, Milford Muskett (Desert Indian with an aversion to canoes!), Mark Stevens, Teri Reese, Jeff Carlson, Brian Garcia and the other Bartenders at the Angelic, Ken Cochrane, Marcia Verhage, Brian Huberty, David Post, Owen Boyle, Tanya Havlicek, Brad, Susan Snetsinger, Neil Euliano at NeuroSolutions, J. Chris Pires, Suzy Will-Wolf, T.S., Volker Radeloff, my family, Chris' family, all the birds in the world seen and unseen by me, Victor Salovarov (Baikal birder of the finest quality), Chessie Rooster Cogburn, Roxy Music Stickland, Sarah and the other members of Poodle Scout Troop 137, Reed Noss, David Quammen, Tom Rooney (publishing fool!), Buzz Holling, James Kay, all the people that turned me down for jobs so that Bernalyn McGaughey could hire me, David Brin and Gregory Benford, the Detroit crowd, Kevin Atkins, Glen Barry (raging against the machine!), Dave McWethy of NOLS, Jim Gage, Derek Hatley, EasyNews, CNN, J. Michael Straczynski, did I mention the PFRC?, Chris Fischer, Smokey Sandfire, and of course, Shasta Ann Lapcat, the finest of felines, may she not only rest in peace, but spend her days chasing mice, chomping birds, and sassing her way up one side of the clouds and down the other, taking no guff from nobody! That should cover it, and if you're not mentioned, sorry, just write your name in here:_______________.

RJM, Federal Way, Washington State, 18 April 2001

PROEM

Robert Rosen, in his 1981 Presidential Address to the Society for General Systems Research presents the case that a systems theoretic perspective provides for strategic innovation more readily than traditional paradigmatic approaches, which are essentially pursuing variations of known tactics. As an example, Rosen presented the story of "The Purloined Letter" by Edgar Allen Poe. The police prefect, in searching a house for said letter, had moved from coarse visual examinations of the residence to fine-scaled probes of walls and couches, which still did not reveal the letter's location. The prefect was using long-accepted police tactics in his search, but his basic strategy, developed over many years of police work and quite successful in most situations, was failing him. The letter, which had been re-addressed and left in plain sight, was hidden in a manner that was outside the purview of the prefect's search strategy. For those readers who don't know the rest of the story, Dupin, the private detective consulted by the frustrated police, found the letter almost immediately upon entering the house by using an new and insightful search strategy. Rosen's point in relating the story is to focus the ineffectiveness of exhaustive yet strategically misguided techniques previously used in pursuing answers to problems. He urges scientists not only to reassess the tactics used, but also reassess the strategic assumptions inherent in accepted data acquisition or technique development tactics.

My point in relating Rosen's talk to you is to propose that this dissertation is less an investigation into wildfire and more an investigation of how modern ecologists approach the analysis of meso-scale processes with a certain strategic ineffectiveness. Specifically, my analysis of the extensive literature on wildfire and wildfire modeling, contained in the Joint Fire Sciences Conference paper presented in Chapter 1, clearly shows that current approaches to meso-scale wildfire modeling mostly involve rescaling existing models. Rescaling extant models exists locked inside a certain strategy, and is therefore fundamentally limited. Do not misunderstand me, simple rescaling of reductionist approaches can produce quite workable solutions within a narrow scale range. However, to solve meso-scale problems in this manner invites casting systems as middle number (Weinberg 1975).

Often, entry into a middle number domain occurs without the investigator noticing. Failure of the rescaled model typically elicits a tactical response, a quest for more detailed data, ever more complicating the original models (e.g., Liu, 1998). Such failures should elicit instead a reassessment of strategy (Rosen 1981). The approach to wildfire modeling in this dissertation is a strategic departure. While the specific discussions, arguments and examples contained herein concern wildfire, the sub-text is using ANNs to deal with middle-number systems. The focus is not the resultant model, it is how does stepping outside of the limits of current models help to model systems of this scale and complexity.

Dissertation Organization

Two basic approaches to producing a dissertation are generally recognized: writing a standard format scientific report with introduction, literature review, data collection, analysis, discussion, and conclusion chapters; or, producing three stand-alone papers suitable for submission to peer-reviewed publications. A hybrid of the two approaches was adopted for this document, combining elements of both while resembling neither.

The first chapter is a paper presented at the Joint Fire Science Conference on 16 June 1999 and recently published by the University of Idaho and the International Association of Wildland Fire in the two-volume proceedings from that conference. The paper outlines the theoretical aspects of meso-scale modeling in general, and proposes a specific approach to, developing a meso-scale wildfire model. The next two chapters document implementation of the proposed modeling approach. Chapter 2 covers data collection and structuring and provides and introduction to basic artificial neural network concepts. Chapter 3 presents some specifics of the modeling environment, outlines model development and presents results. The final chapter starts with a discussion of known, unresolved modeling issues and concludes with a reassessment of the assumptions and theory outlined in the paper, re-casting the model and modeling approach with respect to scope, scale and application.

Questions

As stated above, this dissertation does not follow a standard format, although the departure in format is only a compromise. The following paragraphs are probably more appropriately placed at the end Chapter 1. Since Chapter 1 is a stand-alone paper I elected not to change its content and flow, but instead present the following discussion of assumptions and questions here. The analyses presented here are less a structured study to test hypotheses and more an exploration of a theoretical modeling approach. But, in exploring theory one can often extrapolate results to answer certain questions.

The following is a series of statements synthesized from information contained within Chapter 1 and also in my original thesis proposal . Each statement has questions and analyses associated with it. The analyses were designed to answer the individual questions, while the questions should inform us about the statements veracity.

Statement A: Wildfire spread is controlled by varying combinations of environmental variables. These variables can be hierarchically ordered as fast, moderate and slow acting.

Question A1: Can artificial neural networks (ANNs) learn the controlling relationships between these differently ordered variables for the prediction of wildfire spread patterns?

Analyses: A number of artificial neural network (ANN) models were constructed to address this question, and their predictive abilities were compared. Spatially-distributed variables (e.g., cover type, soils) were presented to the ANN model as a set of raster data files; non-spatial data (e.g., long-term climate variables, windspeed) were either entered by the user or available in a separate datafile.

Question A2: Are wildfire variables that are predictively important controlled by Landtype Association (LTA)? LTAs are meso-scale integrators of many of the moderate and slow environmental variables. Do the important predictor variables for wildfire change with a change in LTA? Do the important wildfire variables change with a change in Subsection, the ecoregional boundaries above LTA?

Analyses: ANN models developed on one LTA were used to predict fires on other LTAs. Trials were conducted on LTAs with similar locational characteristics (e.g., same region of a state), similar environmental characteristics, different locational or environmental characteristics, and combinations of these. The LTAs selected for trial were stratified to also allow analysis of any Subsection changes.

Statement B: Constraints on the spread of any particular wildfire can be classified as top-down or bottom-up, depending on the specific combinations of controlling environmental variables.

Question B1: Can neural networks decide what level of analysis to use in predicting the spread of wildfire? That is, can they capture when a qualitative change in controlling environmental factors occurs and the system changes from one set of constraints to a different set?

Analyses: Working from the models developed from Question 1 (Statement A), a series of qualitative and quantitative evaluations were conducted. Neural network development software allows the user to view what nodes and connections are activated to produce the resulting output. Qualitatively, then, one can track which

> set of input variables combined to produce the models response. More quantitatively, an ANN model developed using only relatively small fires (but a full range of environmental variables)can be tested against a large wildfire. While the predicted output can be directly compared to the actual fire, by analyzing the internal workings of the network one can determine how the fundamental relationships learned from the smaller fires (contained in the network weights and structure) combine in the prediction of larger fires. Perhaps the conditions for fires to become large is a prediction in itself.

The chapters in this document describes the starting phase of a lifetime of potential research questions. I feel the work has just started, and this dissertation describes what I did in response to these questions, but also presents where I think this research will go.

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Toward a Theory of Meso-scale Wildfire Modeling - a Complex Systems Approach Using Artificial Neural Networks

Abstract

Wildfire occurs over a wide range of spatial and temporal scales. Typically. patterns of wildfire spread are modeled using fine-scale, mechanistic equations or broad-scale, probabilistic equations. Both modeling approaches use some form of fuel. climate. and topography variables. Mechanistic approaches look at the small scale constraints (e.g.. percent of moisture in fuel) that enable a fire to keep burning. In probabilistic models fire spread is determined by the size and connectedness of fuel patches distributed across the fire landscape. Both approaches assume the fire behavior environment is a simple system that can be described with simple equations. but that assumption holds true only over a very narrow range of scales. A complex systems approach to modeling fire behavior involves not

only knowing what variables are constraining fire growth at a fine scale but also which constraints are absent at a broad-scale, allowing a fire to spread unchecked. Possession of highly detailed information on system variables will not inform you where the system is going because small changes in the context will change the importance of certain variables. What is important are the cross-scale relationships between the upper-level context and lower-level constraints to the predictor variables of the model. Existing fire models lose predictive power when subtle shifts in environmental variables cause qualitative changes in fire behavior, that is, when the system's behavior changes scale. Artificial neural networks (ANNs) are designed for problems with cross-scale relationships that produce non-linear changes in system behavior. The ANN framework provides a comprehensive integration across scales of fire environment variables. The ANN is able to determine the equations describing those cross-scale interactions and better predict where a fire will spread as a result. This better predictive capacity is needed in light of global climate change and increasing human habitation in rural areas.

Introduction

The need for a meso-scale wildfire model stems from a Forest Service initiative to assess and analyze fire-regulated ecosystems in the northern Great Lakes States. Forest Service research activities in the Lake States have included fire occurrence factor analyses (Cardille 1998) and disturbance regime mapping for certain subsections within Province 212 (Keys, et al. 1995). A useful fire model should be appropriate for use on National Forests and surrounding lands within the Province and facilitate the development of alternative strategies for ecosystem management. Linking the model to a forest succession model will aid in planning and evaluating burning as a land management practice.

We model fire to better manage fire and its effects on ecosystems, communities and landscapes. Some fire models are stand-alone while others are modules within larger land cover dynamics models. Extant fire models operate at many scales, use different predictive equations, and produce numbers or maps representing fire frequency, severity, spread rate, burn pattern or risk. A meso-scale fire model is needed for several reasons. Many fire models were originally developed for the conifer-dominated forests of the western U.S. Ecosystem differences (e.g., wind/elevation interactions, landform and cover type characteristics, etc.) may make these model structures inappropriate for the Great Lakes ecoregion. Wildfire modules within larger forest succession models lack the resolution required for most forest-level management and planning efforts. Increasing human presence on and around forested lands in the region raises the potential for conflicting land management scenarios (Plevel 1997). Therefore, forest land managers recognize the need for a wildfire model specifically applicable to the northern Great Lakes ecoregion.

The unique aspect of this model is the use of an artificial neural network (ANN) as the decision-making engine. An ANN-based wildfire model is distinctive in comparison to contemporary models. Extant fire models have their strong points, but ANN models offer advantages for some data availability and field situations in two ways. First, they integrate relationships between fire environment variables (fuel, topography and climate) relating to fire behavior that occurs at multiple spatio-temporal scales. Second, they allow the capture and analysis of cover, landform and climate interactions that may be unique in time and space with respect to predicting fire spread.

The ANN model structure should be robust in predicting wildfire burn patterns over the range of fire environments present in the ecoregion. Traditional modeling approaches require that the rules relating input to output be known *a priori*. Accuracy of the predicted variables relies on the precision of the input variables, so a lack of data for one component module or equation will cause the whole model to fail. In contrast, ANN models need no explicit statement of the rules (they will be learned via inductive reasoning), are fault tolerant (due to redundancies within the network), and can function with noisy or partial data.

Artificial Neural Networks

Haykin (1994) defines a neural network as ". . . a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use." Artificial neural networks acquire knowledge by learning from examples and store that knowledge as synaptic weights in connections (networks) between processing nodes (neurons). ANNs have the ability to model complex functional relationships predefining the behavior and interactions of all the pertinent components (i.e., the rules are not known). The pattern emerges through positive feedbacks that eventually press against global constraints that define structure. ANNs reduce the need to write "rules" based on expert knowledge. Neural networks determine these rules by mapping directly from input to output with a blind, but effective, search strategy (Sui 1994). A trained network can respond non-linearly to input values, where a small change in one or several inputs can result in an exponentially greater output response. Conventional modeling techniques do not readily do this unless the relationships are known *a priori*. Since their inception, artificial neural networks have been trained to perform tasks that appeared impossible for conventional computer programming techniques, for example, steering a car under new or unknown conditions, reading hand-written postal zip codes, or recognizing spoken language (Dukelow 1994).

Basic ANN Architecture

Conceptually neural networks are quite simple and can be represented as graphs composed of a series of linked nodes (Figure 1.1) that represent biological neurons and their connections. Multi-layered, feed-forward networks are acyclic graphs and have a series of nodes arranged in layers (input, hidden and output), with links between every node in adjacent layers (Figure 1.2). Full connectivity is not a requirement for a functioning neural network. There are typically only one input and one output layer. A network with one hidden layer can learn most continuous functions, while multiple hidden layers can learn discontinuous functions (Russel and Norvig 1995). Each link in the network has a numeric weight, the strength (value) of which

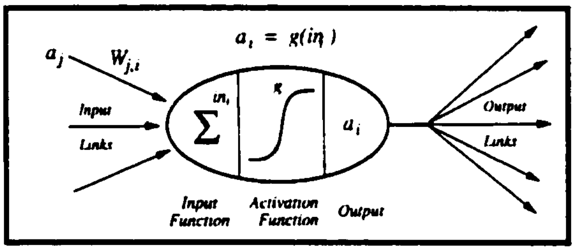

Figure 1.1 A neural network processing unit. (Adapted from Russel and Norvig 1995)

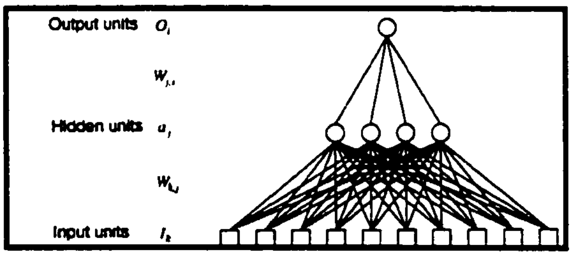

Figure1.2 A single-hidden layer feed-forward artificial neural network (Adapted from Russel and Norvig 1995)

relates to the local node's effect on the whole network. Input values are multiplied by the weights of the input links leading to each node in the hidden layer (Figure 1.1). Each node in the hidden and output layers performs two functions: a linear summation of the weighted inputs and then a nonlinear transformation of that sum using an activation function (Russel and Norvig 1995). The activation function produces an activation value for each hidden node that is "fed forward" to the output layer. The nodes of the output layer also calculate a weighted sum, and the activation function produces the output value.

Qualitative Analysis of the Fire Environment

Wildfire occurs over a continuous spatio-temporal range (Simard 1991; Turner and Dale 1991). The elements of the fire environment triangle - fuel, weather and topography - also vary continuously over the range of scales that wildfire occurs. Approaches to modeling wildfire spread patterns are either fine-scale mechanistic or broad-scale probabilistic (McKenzie, Peterson and Alvarado 1996). While both approaches correlate observed fire behavior with fuel, climate, and topography variables, they only work within a narrow, fixed-scale range. Mechanistic approaches scale locally to what keeps a fire burning, while fire spread in probabilistic models is constrained by the rate of percolation across the landscape. To work within a meso-scale range, both approaches extrapolate model results up- or down-scale, or aggregate fire environment variables to the desired scale of analysis. Extrapolating up-scale from physically-based equations or down-scale from statistically-derived landscape variables results in less predictive power because the relationships between the fire environment variables change in a complex, non-linear manner as the scale shifts away from that of the original model. Changing spatial and temporal scales of fire environment variables leads to the inherent unpredictability found in middle number systems (Weinberg 1975; Allen and Starr 1982).

Small number considerations, like our planetary system, are predictive because one can account for the behavior of each component with one equation for each part. Large number systems, e.g., the gas laws, have so many parts ($N > 6.02 \times 10^{23}$, Avogadro's number) that statistical techniques are employed to predict overall system behavior based on the assumed average component. Middle number systems lie between the domains of these two approaches; there are too many components to account for the behavior and interactions of all the parts, but too few to permit the assumption of uniform behavior. Middle number systems are extremely sensitive to initial conditions because any component or process may enter into feedback and come to dominate system behavior.

Fire literature has focused on either the constraints on fires raging or the constraints on fires surviving, but not both sets of constraints. Each class of model is predictive to a limited degree. What is needed, and what ANNs provide, is prediction in the context of both sets of constraints simultaneously. Switching constraints, however, means predicting within a middle number domain where one set of constraint factors is historical, and the other can be captured in a relatively mechanistic account. Since history and mechanism are not compatible, our meso-model cannot be purely mechanistic or probabilistic. In the middle number domain, fixed scale simulations or fine-scale, physically-based models lack sufficient flexibility and miss important dynamic interactions. Predictive modeling of fire behavior involves knowing what variables are constraining fire growth or which constraints are absent allowing unchecked positive feedback between fire and fuel. Extant fire models lose predictive power when subtle shifts in environmental variables cause a qualitative change in fire behavior.

Most modeling approaches select and theorize about environmental parameters based on observations and expert knowledge. Parameters are calibrated using reasonable assumptions and probabilities to incorporate processes that are well understood or easily encoded. Once calibrated, parameters are dealt with as constants in models. This fixes the scale over which the model is valid and limits the resolution. On average, working models behave as expected and give solid results when parameters do not exceed their normal range. Models often fail to predict larger events because those events lie beyond the averaged model parameter values and the process is initiated by a low probability, but ecologically possible, alignment of environmental conditions. Fixed-scale models are often inflexible, only valid within a narrow state space, and provide inadequate responses during conditions when the modeled system switches from being controlled from below by internal processes to being controlled from above by external constraints.

System Scaling

O'Neill, et al. (1986) show that hierarchy theory (Allen and Starr 1982), when applied to ecosystem processes and functions, can provide a useful approach to situations that appear middle-number. By empirically determining and hierarchically ordering the system rate variables, we limit the imposition of predetermined, human-based scales on our analyses. In discussing fire and insect effects on boreal forest ecosystems, Holling (1981) describes a simulation model that requires equations with 78 variables to predict adequately spruce budworm dynamics in only one forest patch. With 393 patches in the affected area, a comprehensive simulation model would contain more than 30,000 variables. Using a topological approach, the 78 local variables reduced to three rate sets relating to budworms (fast, months), foliage condition (intermediate, years), and crown volume/hectare (slow, decades).

While the topological approach is qualitative in nature, it is very instructive in understanding how and why system dynamics change with a change in variable values. Where the simulation model provides detailed, essentially mechanistic, explanations of what happens in the system, its complexity precludes understanding how and why results are produced. Holling (1981) presents a similar topological analysis of fire (Figure 1.3). Fire intensity is the fast variable, fuel intermediate, and trees slow. This simple model shows an equilibrium manifold (solid line) where the region to the left of the line represents conditions where self-sustaining fire is not possible. Along the curve and to the right, fuel conditions and fire intensities are sufficient to sustain combustion. The line at B represents the average intensity of random ignition events. Fuel conditions less

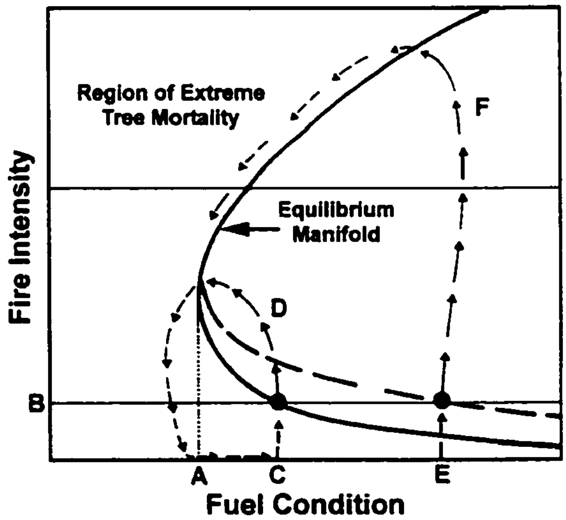

Figure 1.3 Fire environment manifold. (Adapted from Holling 1981)

than A do not allow sustained fire under any intensities. As fuel condition increases toward C, the regular, random ignitions would result in a self-sustaining fire whenever C was reached. Fire suppression or changing climate deflects the lower arm of the equilibrium manifold upward, preventing sustained combustion at lower fuel conditions (slow variables constraining fast). Over time tree crown cover increases, creating conditions capable of sustaining a crown fire, a significant change in state of the intermediate variable. Eventually a hot, dry year will occur, and while fast atmospherics still control the fast fire variables, previous slow variable constraints have set the stage for large scale conflagration (Figure 1.3, E to F). The manifold in Figure 1.3 assumes that tree density, the slow variable, is in some type of equilibrium; the manifold aids in understanding why a landscape experiences regular and periodic fires of moderate intensity (D) despite frequent, random ignitions.

Fire behavior always involves the question of what variables will be controlling, providing the constraints on fire, or which constraints are absent, allowing unchecked positive feedback between fire and fuel. Fixed-scale simulations or fine-scale, physically-based models lack sufficient flexibility and will miss important dynamic interactions. Management use of these models will result in surprise (Holling 1986). By ignoring spatial aspects and folding other temporal variables into only three, topological analyses offer an understanding of fire behavior at any spatial scale (e.g., needle, tree, stand, forest). Atmospheric variables can also be represented as fast (relative humidity, precipitation), intermediate (seasonal temperature and annual precipitation), or slow (climatic averages over decades or centuries) (Figure 1.4).

Fire models based on Rothermel's (1972) equations use fast atmospheric variables to predict fire intensity with fuel models that implicitly incorporate intermediate and slow climatic variables (Figure 1.4). Rothermel's analysis (Rothermel 1991) of model predictions during the 1988 Yellowstone fires shows how reliant the equations are on fast/fine scale information. Extant models appear to map between fire and landscape but only weakly to atmosphere, or between fire and atmosphere but only weakly to landscape. These models make only simple connections between the elements in Figure 1.4 over a narrow scale range. An adaptive model would seek connections across multiple scales, creating pathways among all levels of slow-intermediate-fast and micro-meso-macro variables.

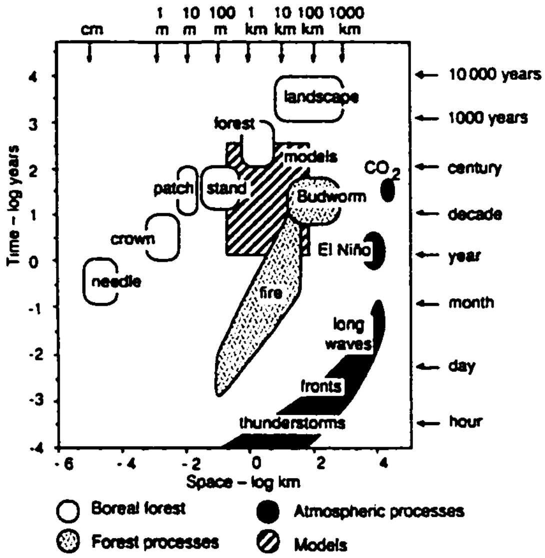

Figure 1.4 Time and space scales for the boreal forest and their relationship to some of the processes which structure the forest. Contagious meso-scale disturbance processes provide a linkage between macro-scale atmospheric processes and micro-scale landscape processes. (Adapted from Holling, et al. 1996)

It is easy to extrapolate the manifold line (representing a compression of the other variables in a complex fire environment, Figure 1.3) to an n-dimensional space, and hypothesize that subtle shifts in several variables will shift the bottom of the manifold up or down, crossing B at different locations. This complex view of fire is well modeled with ANNs, since fast, intermediate and slow variables can be somewhat isolated within the network, having only minimal connectance to other portions of the network. The ANN framework provides a comprehensive integration across scales of biotic and abiotic variables. The actual equations describing those cross-scale interactions are contained in the weights of the network.

Extant Fire Modeling Approaches

All fire models look at fire spread from the standpoint of the flames pushing the fire front along if fuels are available or wind is strong enough. Results from some fire spread models suggest that different upper-level elements are controlling under varied environmental conditions (Green, Tridgell and Gill 1990; Gardner, et al. 1996). Through repeated simulations these models can determine the degree to which a given landscape is connected (i.e., able to carry a fire), when it is above or below some critical threshold value (Green 1994; Turner, et al. 1989). Information on percolation thresholds is needed for fire management of present-day landscapes and should be incorporated into wildfire models. Indeed, Turner and Romme (1994) and others (Simard 1991; McKenzie, Peterson and Alvarado 1996) discuss the need for a link between fine-scale mechanistic and broad-scale probabilistic wildfire models. They point directly to the essential need to be able to determine when landscape pattern or fire-line thermodynamics provides the more important constraint on wildfire spread.

Wildfire models (e.g., Andrews 1986; Finney 1996; Gardner, et al. 1996; Clarke, Brass and Riggan 1994) operate by encoding endogenous fire processes (e.g., rate of spread, intensity, etc.). While each fire model has different, specific input requirements, any model of wildfire will require, in general, fuel, weather, and topography data (Fons 1946). What is usually neglected in mechanistic models of wildfire is the overlying landscape structure and variable climate that serves as context for and constraint on disturbance processes (Allen and Hoekstra 1992; Holling, et al. 1996; Simard 1991).

For simplicity ecosystem models usually only incorporate two hierarchical levels (Holling 1995). Incorporating fire regime into these model sets intermediate variables of fuel and weather as the lower-level context; the model then simulates effects on forests with variation in climate (both, higher-level, slower-acting variables). Alternatively, physically-based fire models encode low-level, fast combustion processes and scale-up to stands and forests. Local, human impacts on the biosphere are having global effects (e.g., rising CO_2 levels), crossing scales and ecological disciplines. Human society is now acting on a scale and at a rate equivalent with ecosystems, so our models must start to include variables from more than two hierarchical levels. The difficulty in modeling these effects has been in connecting processes operating at vastly different rates (Allen and Starr 1982). Encoding each process with its own time step would be cumbersome and lead to very complicated models. Even if the computer code could capture the details of a single process, the cross-scale interactions of different processes are not likely to be known or knowable.

Other Approaches to Modeling Fire

Other recently developed models have taken advantage of raster-based simulation concepts (e.g., cellular automata (CA) and nearest neighbor decision rules) to incorporate concepts of diffusion (Clarke, Brass and Riggan 1994), percolation (Green 1993b), or contagion (Li and

Apps 1996; Gardner, et al. 1996) in spreading fire across a landscape. CA are a 2-dimensional array of cells with values that represent the global state of a variable. Each cell is a computer and updates its state at each time step based on the state of its neighbors (Green 1993a). Limiting interactions to immediate neighbors makes CAs easy to computerize, and the efficient processing is often used to model complex systems (Karafyllidis and Thanailakis 1997). Most CA models of fire spread require some estimate of the burn potential for each cell prior to running the model. The probabilities are often stochastic in nature, and multiple runs are used to develop a map of fire risk. Cellular automata have been implemented in fire models using Rothermel's (or others) rate of spread (Ball and Guertin 1992; Karafyllidis and Thanailakis 1997), Huygens' principle (French, Anderson and Catchpole 1990), nearest-neighbor movement rules (Bryant, et al. 1993; Ratz 1995) and invasive epidemic processes (Green, Tridgell and Gill 1990). Clarke et al. (1994) present a unique method of fire propagation in a CA.

Using only local rules means that the emergent pattern often represents what is physically possible, though not necessarily ecologically allowable (Allen and Hoekstra 1992). CA fire models often produce distorted or unnatural fire boundary shapes (French, Anderson and Catchpole 1990; Ball and Guertin 1992). By using only nearest neighbor rules, CA models do not incorporate a context, the ecological constraints that limit the total range of physically possible to a smaller subset of ecologically allowable structural and organizational configurations. The ANN model, while grid-based, makes local decisions but also incorporates information from the surrounding landscape to provide a context.

Concepts of Ecosystem Change

Humans, fire, wind, disease and insects are the major agents of change in forests. Fire is a perturbation at the scale of a tree, while at the scale of a forest, fire is an integral, endogenous ecosystem process (Allen and Starr 1982). While fire kills individual trees, it initiates a cycle of stand renewal, often ensuring the survival of the tree species. Fire operates over multiple spatio-temporal scales, and characteristics of the variables that control fire behavior also vary in time and space. Topography is relatively stable over time but exhibits great spatial variation. Fuel and climate vary in both time and space. Fuel is stored energy on the landscape (Sapsis and Martin 1993). Fuel state describes the moisture content of live and dead fuels. Change in fuel state can be rapid (daily) or intermediate (seasonal/annual). Fuel type refers to species, spatial arrangement (vertical and horizontal) and density. Fuel accumulation after a fire is generally a slow process that can continue for 100 years or more, although some disturbances (insect outbreaks, disease, windthrow) will cause more rapid fuel accumulation.

Fire alters the condition and arrangement of abiotic and biotic elements on a landscape, and species respond to the changed environment. The type of vegetation that returns after a fire determines in part when fire will return and how severe its effects will be. This positive feedback loop between species and fire can develop into a relatively stable system over time, assuming that large scale climate (the upper-level constraint) remains constant. With shifting climate, human impacts and exotic invaders, present day fire regimes cannot be readily discerned from historical data (Schoonmaker 1998). Management must decide what ecological effects they want to produce with fire, and determine an appropriate fire regime to meet those expectations (Pahl-Wostl 1998). The scale of the underlying disturbance regime(s) and the physical space on the landscape required for disturbance processes to occur are important factors to consider when developing any meso-scale model of fire.

Rowe (1983) identified five life history mechanisms that plants use in response to different fire regimes. In areas that experience a range of fire severities, a species may employ several of these strategies to survive. Fire suppression favors avoiders and results in densely stocked, late successional forests. The key point is species are not the relevant entities with respect to fire regime, rather Rowe's strategy categories are. Fire interval will equilibrate through positive feedback with vegetation (ordered along Rowe's strategy categories) to maintain fire intensity and severity. Fire intensity is a fast, local variable (low level dynamics). The lag in the period over which fuel accumulates on the landscape (intermediate variable in space and time) acts to constrain intensity.

To achieve environmental constancy (i.e., an equilibrium) one is required to fix scale in space and time. By averaging variability in time and graininess in space, an emphasis is placed on nature as a constant over time. This leads to management policies that are unprepared for and surprised by change (Holling 1986). Figure 1.5d represents an equilibrium-centered view of the material world where the ball, i.e., environmental variables, always returns to a single stability point following disturbance (Holling, et al. 1995). A more dynamic view of change (Figure 1.5a) incorporates multiple stability points. Equilibrium views assume linear causation wherein a small change in an environmental variable causes only a small change in system state. Multiple stable equilibria indicate spatial and temporal variability and nonlinear causation. Planning and policy derived from an equilibrium basis will not recognize stable configurations beyond the one in which the system resides.

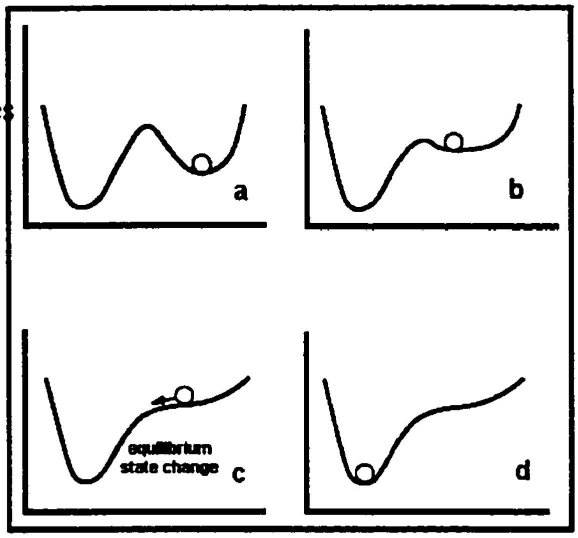

Figure 1.5 Equilibrium diagrams. (Adapted from Holling, et al. 1995)

Continual, constant environmental change displaces the ball short distances over time (Figure 1.5b), yet the system state appears to be within the same basin of attraction (linear change in environmental variables). Further small changes in the environment result in a sudden, nonlinear change in state, with the system moving to another stability point (Figure 1.5c), a surprise from the equilibrium viewpoint (Holling 1994).

Complex Systems: a Point of Departure

Mechanistic models of single processes are often powerfully explanatory in regard to the behavior of individual system components, but attempts to assemble satisfactorily predictive, unified models from these components have been largely unsuccessful (Ulanowicz 1997). The ability to predict whole system behavior from mechanistic models fails because it is impossible to anticipate and account for the effects of every subtle aspect of system behavior. Current ecosystem and disturbance models are constructed in an explicit manner, defining exactly how modules and equations and variables react and interact. The whole system in its infinite detail is not the right referent; the focus should be on prediction with regard to phenomena (Allen and Hoekstra 1993).

The questions asked of ecological systems often generate middle number models (O'Neill, et al. 1986). Attempts to seek mechanistic causes for overall system behavior through the approaches favored by traditional hard science cannot yield explanations and quantitative answers that are definitive when a middle number system is invoked. Funtowicz and Ravetz (1994) have noted that cause and effect explanations have limited power because in complex systems these categorical distinctions disappear. Ecological systems invite casting them as complex, and complex systems require different causal models. A complex systems approach incorporates the explanatory power of positive and negative feedbacks and the recognition of the emergence of hierarchically self-organizing and self-sustaining structures to characterize system behavior (Holling, et al. 1996). Because complex systems do not permit the definitive answers of traditional hard science approaches, a methodology of complex systems is needed to provide soft answers with good explanatory power.

Disturbance regime and landscape equilibrium are powerful concepts in understanding community and ecosystem development through time. Quantifying regime or equilibrium require that space, time, or both be fixed so that the concepts are scale dependant (O'Neill, et al. 1986). There is also the assumption that climate and vegetative composition do not change significantly. Regimes are typically presented as averages for a landscape when they actually come from multiple disturbances of varying severity, size and season. Regime-based models are very instructive in the analysis of historic landscapes or gaining insight on potential future patch dynamics. They are not, however, highly informative for current forest management and planning, because the forested landscapes and vegetative communities from which the regimes derive no longer exist (and probably will never again), the spatial presence of species on the landscape has changed, new species have been introduced, native species have been greatly reduced or eliminated, climate has changed or is currently changing, humans have greatly increased ignition sources, and human intervention (suppression) alters final fire size and shape. Fire regime needs to be predicted from a model, not be an element within a model (Li and Apps 1996).

ANN models address these concerns. The non-linear response nature of ANN architecture facilitates learning and generalization on a wide range of input and output values (Haykin 1994). An ANN can accept categorical data as well as continuous. Assumptions about the distribution and independence of the input data are not as vital to constructing an effective network as they are to more conventional statistical analyses (Sui 1994). The changing spatial and temporal scales of fire environment variables used in modeling wildfire in the Lakes States present the modeler with all the problems inherent in middle number systems. Employing ANNs allows modeling the meso-scale fire environment in a highly powerful and predictive manner. Even though on the face of it the system appears middle number, the ANN explores system structure until, at an appropriate level of analysis, prediction becomes possible. The ANN recasts the parts of the question so that behavior becomes reliable. It filters out middle number specifications by elimination of pathways that do not provide repetitive behavior.

Fuel Models

Rothermel's original equations assume that the fire is burning through a uniform fuel, across a flat terrain with no wind. These simplifying assumptions made the original specification of fire behavior equations possible. Mechanistic fire models based on Rothermel's equations inherited those simplifying assumptions. Fire behavior research over the past 30 years has dealt primarily with how to translate the relationships found in the simple fire environment of a test laboratory to the very complex fire environment found in the outside world.

We need to accept that the highly controlled conditions found in a fire behavior laboratory are rarely if ever found in managed ecosystems. The landscapes that humans manage fire on have highly complex fuel associations, variable terrain, and unpredictable weather conditions. A new theory of meso-scale fire modeling must start with the foundational assumption that the fire environment is complex and varied. Predictions in fire environments beyond Rothermel's fine-scale equations are accomplished by adding modifying parameters to the original equations. This *elaboration of structure* is considered mere complication by Allen, et al. (1999). The proposition here is an *elaboration of organization* when assessing real fire environments. Our hierarchical complexification, as distinguished from complication by Allen, et al. (1999), in the analysis of fire accepts and incorporates the differing spatio-temporal resolution of the fire environment variables. Input data can be maintained within a GIS as close as possible to original scale and resolution, and ANNs can be used to learn the cross-scale relationships between those fire environment data. What it all comes down to is we collect very fine-grained field data on fuel composition, and then dilute the precision of those data by lumping them into fire behavior fuel models that fit known equations. The lumping hides switching constraints inside the aggregates, generating middle number effects. ANNs preserve the original data resolution and develop a complex, continuous function to describe the fuel landscape.

It is ironic that the decades-long effort to produce a spatially-explicit model that accurately predicts fire behavior has pushed input data requirements beyond that which the typical end user is able to provide. Fuels vary continuously across the landscape, but current concepts of fuel models require human judgement to assign fuels to discrete categories. Each evaluation becomes a separate constraint on the model. What is needed is a new theory of fuel models to inform a complex systems methodology that integrates the three elements of the fire environment triangle into a robust, continuous description of fire fuel.

Since one cannot directly measure fire behavior fuel models (FBFMs) in the field, Keane et al. (1999) hypothesized that FBFMs could be related to the biophysical environment, species composition, and stand structure. Results show that while one can accurately map the biophysical, species and stand properties, the relationship between these elements and FBFMs is not well known and thus the derived fuel model layers had low accuracy. A knowledgeable and experienced team achieved only a 50-70% accuracy rate in developing FARSITE input layers on 1.5 million acres of the Gila Nation Forest (Keane, et al. 1999).

Results from the Gila National Forest mapping effort indicate that a different approach to describing fuel on the landscape is necessary. Fire environment variables should be mapped at a resolution appropriate for the variable in question and kept as close as possible to that original scale. FBFM categorization, via multi-step classification and aggregation procedures, dilutes the precision of the original data. Fuel landscapes are composed of more than the vegetation on them; that vegetation also has a history associated with it (Havlicek 1999). FBFMs can be modified to incorporate short-term weather, but climatic factors vary during the entire lifetime of the vegetation, subtly (or not so subtly) influencing fuel loading. The cross-scale interactions between landscape and climatic processes need to be directly addressed in any model of fire fuels.

As discussed earlier, artificial neural networks are very appropriate for use in analyzing data where the relationship between the inputs and outputs is not well-known. How the fuel landscape was influenced by climate during its early years of development versus its middle or later years is not easily quantified, but can be inferred from weather records, past and present vegetative spectral response, landscape position, timing and type of non-stand replacing disturbances (harvesting, disease, pests, residential development), and inventories of current field conditions (e.g., the three aspects mapped with reasonable accuracy on the Gila National Forest). Using an ANN, spectral data from Landsat TM or other remote sensing platform (historic and current imagery) could be input directly, along with field-based mapping of other fire environment variables.

Raw digital numbers from unclassified satellite imagery are the closest we can come to a continuous valuation of landscape fuels, and various sensors integrate spectral response over different spatial and temporal scales. When sub-five meter imagery and radar data become readily available, spectral characterization of fuel landscapes would be possible over almost the entire range of human fire management interests, allowing the development of a consistent, hierarchically-organized, multi-scale fuel model developed for the continent but scalable to regional and local considerations.

To further establish the context in which the fuel landscape developed, additional model input layers may include: surficial geology or soil texture; Landtype Association (LTA) (Jordan, et al. 1996); precipitation (day, week, month and yearly totals); hydrography; elevation, slope and aspect; time since last fire/disturbance; land use/ownership; fire suppression regime; road density; and human population/housing density. Some or all of these elements may be important context for or constraints on fire spread. This floating scale approach to fire and fuel modeling has implications for local, regional and state forest planning, and also can be useful in rapid assessments of fire risk, pointing to areas requiring more finely-scaled analyses.

Conclusion

Over the last decade, C. S. Holling developed and refined (Holling 1986; Holling 1992; Peterson, Allen and Holling 1998) a four-box model describing how ecosystems function (Figure 1.6). The first two boxes refer to the classic ecosystem life cycle stages, from

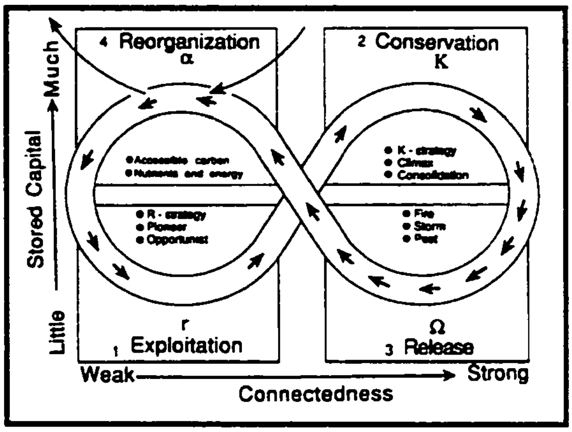

Figure 1.6 Holling's figure-8 model of ecosystem change.

colonization after a disturbance (Box 1: exploitation) through succession proceeding toward climax (Box 2: conservation). This cycling of vegetation from disturbance to climatic/edaphic climax and back to disturbance was the traditional view of ecosystem succession in the first half of the 20th century (Clements 1936). Studies from various researchers in the early 1980's have served to shift our understanding of succession to a more dynamic process (Holling 1992).

Holling (1992) makes four points: 1) following disturbance and during succession, invasion by persistent species can be highly variable and dependant on many random factors; 2) early and late successional species can and will maintain a presence on the landscape through time; 3) disturbance events of varying sizes are part of the ecosystem and affect the timing of succession; and 4) there are multiple potential climax types (stable attractors), and some disturbances can move an ecosystem between attractors (Kay 1993). Recognizing that there is not a unique successional pathway for a given landscape prompted Holling (Holling 1986) to add two additional elements to the model, release or creative destruction (Box 3) and reorganization (Box 4).

The release and reorganization phases of the model have the greatest influence on what successional pathways will recur in the system after disturbance. The accumulation of a large amount of stored capital (e.g., biomass) and organization (e.g., structure and feedback) in the conservation phase eventually leaves the system overconnected (Allen and Starr 1982) and susceptible to some agent of change (e.g., fire). The shift from conservation to reorganization is rapid. The post-disturbance, weakly connected system is now free to exploit the released capital and begin the exploitation phase again. If there is sufficient capital (e.g., organic matter, nutrients) and information (e.g., seed source) left in the system and its surroundings following disturbance, succession may return to its predisturbance trajectory (O'Neill, et al. 1986). If the disturbance is great in extent or severity (i.e., most of the capital or information is lost) the system can change qualitatively from one successional pathway (attractor) to another (Ulanowicz 1997). The arrows into and out of Box 4 signify the possibility for change in ecosystem processes, an escape to another basin of attraction where a qualitatively different four-box model describes the system.

The four-box model of birth, growth, death and renewal processes spans many scales. The figure-8 describing processes within a single forest stand has smaller figure-8's nested within it (e.g., individual tree birth, growth, death and decomposition) while the stand figure-8 is nested within a larger, regional-scale four-box model. The S-curve dynamics and multiple disturbance types, incorporated into the four-box ecosystem model, would show that disturbances can act serially to effect a change greater than would have occurred if each disturbance was modeled independently.

Holling (1986, 1995) presents different viewpoints that aid in understanding whence come societal perceptions of ecology and how these relate to management. An equilibrium-centered view assumes nature is constant or only changes slowly so human knowledge and technology can keep up - resources are never limited (Nature Cornicopian) because we invent substitutes. A second view is that of dynamic, Nature Resilient, with multiple stable states, variability, heterogeneity and instability - it accepts that complete knowledge of the system is unattainable and management must allow variation and maintain resilient structures in the process of extracting benefits. From this viewpoint we can chart a course of societal change and management that transitions to a sustainable human presence. Alternatively, Holling's four-box model focuses more on Nature Resilient with nested cycles of order and collapse, renewal and innovation. A final, emerging viewpoint, Nature Evolving, comes out of the more recent sciences of chaos, complex systems analysis, self-organizing systems, nonlinear behavior and discontinuous change.

From analyses of historical management practices and modifying Holling's four-box model, Gunderson et al. (1995) present a general model of ecosystem management. A cycle of four phases is described: 1) exploitation (management to facilitate progress); 2) canalization (management is static, while ecosystem changes with society); 3) crisis (environmental surprises and social conflicts arise); and 4) reorganization (management learns and adapts to new configuration). The Nature Evolving viewpoint seeks interdisciplinary, adaptive institutions that understand that constraining natural variability reduces the resilience of ecosystems (Holling 1995).

The history of fire management in the U.S. has experienced several of these cycles on a local and national basis. With global climate change, El Nino events, and six billion people demanding resources from our forested lands, fire's role as a management tool is probably approaching crisis. The inevitable reorganization phase will need adaptive models. We anticipate that our approach to wildfire modeling will have significant impact on how we manage fire-susceptible lands and human actions on them. With proper design, the model interface will allow fire managers to update the ANN with each new fire, allowing the model to change incrementally with time (hopefully tracking fire regime changes in real time). The influence of short-term (days or weeks) and long-term (years or decades) climate, vital environmental constraints, could be assessed and directly incorporated into the ANN. These evolutionary abilities of the model will prove useful in light of the uncertainties of global climate change. Furthermore, by decomposing the ANN weights we hope to find the environmental factor thresholds that, once crossed, allow fires to escape suppression and control efforts. An ANN-based modeling approach will determine what factors control fire on a given LTA, watershed or forest, and whether those factors are the same or different on each landform analyzed.

Recognition and characterization of the emergent properties of wildfire (Green 1993b) with changing controlling factors are vital to developing long-term ecosystem management strategies. By not incorporating these concepts managers will continue to be surprised by, and unprepared for, catastrophic wildfire events.

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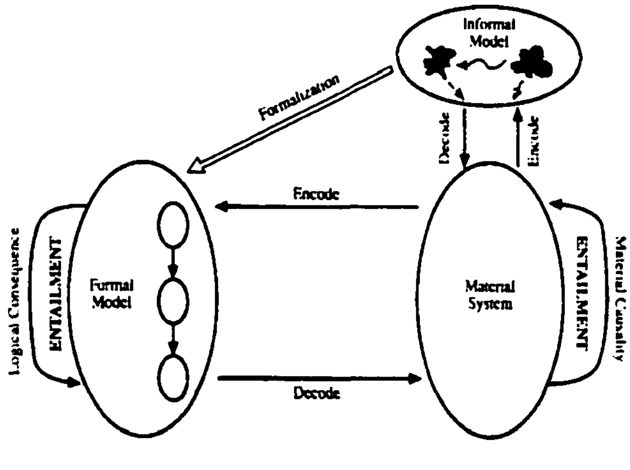
1.5

Models, Fire and Models of Fire

As discussed in the Proem, the first chapter is a stand alone paper that was space-limited by the proceedings editors. This chapter serves to supplement the theoretical framework outlined in the first chapter and presents a deeper exploration of the relevant modeling and fire literature. There are a few paragraphs that repeat portions of the first chapter, a necessary compromise to maintain the flow of ideas in this chapter. After working through modeling approaches, fire fundamentals, extant fire models, and inherent model assumptions, we arrive, at the end of this chapter, at the crossroads of fire scale and fire theory.

Models and Modeling

Much of what we do as humans and as ecologists is formulate models about systems. Models are intellectual constructs for organizing experiences (Allen and Starr 1982). Most models are informal thoughts about how the material world works based on our observations of it (Figure 1.5.1). Informal models guide us in developing research questions or



The material system appears coherent because it is entailed by material causality. The formal model is coherent through entailment by logical sequences. In ecology, we appear also to use informal models that are eventually formalized for testing and experimentation. The material system maps to the model through encoding. The formal model maps to the material system by decoding.

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Figure 1.5.1. (Adapted from Allen 1998)

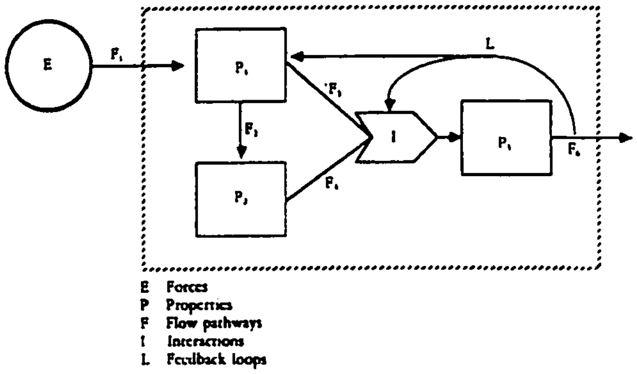
making predictions such as how soon that thunderstorm will arrive to douse the fire in the barbeque pit. Some informal models become laws written down by experts with extensive knowledge, but remain informal models. When informal observation is translated into logically, internally consistent rules or algorithms, they are considered formal models that describe some aspect of the material system (Allen 1998).

The knowledge base for a material system may be extensive, but complete knowledge is not possible (Rosen 1991) and complete encoding of what is known is usually impractical. Formalization involves deciding what aspects of the system are vital in producing a good quality representation and which are less necessary or informative. The formalization process is probably the most difficult and important part of modeling. A formal model's operation (decoding) informs us about the verity of the assumptions comprising it (Allen 1998).

Elements of Models

Jorgensen (1997) discusses five components that could be contained in a mathematical model of ecological processes. *Forcing functions* are external functions or variables that affect the state of a system. They can be input variables under the direct control of the modeler or be stochastic functions that influence system processes in a random manner. *State variables* are typically observed as model results, the variable(s) of interest. *Mathematical process equations* in the models relate the state variables to the forcing functions and the model predicts the effect a change in an external variable has on the system state. *Universal constants* such as atomic weights or Avogadro's number are often used in model equations. *Parameters* are coefficients in the process equations.

Looking at models from a more general perspective, Odum (1989) refers to informal and formal models having forcing function (*forces*) and state variables (*properties*) as components, but also *flow pathways* for the transfer of energy or material. These flows are controlled or modified by interactions of properties and forces (*interaction functions*) and *feedback loops* that influence components and flows. The detailed components that Jorgensen describes are sub-components in Odum's ecosystem model diagrams (Figure 1.5.2).

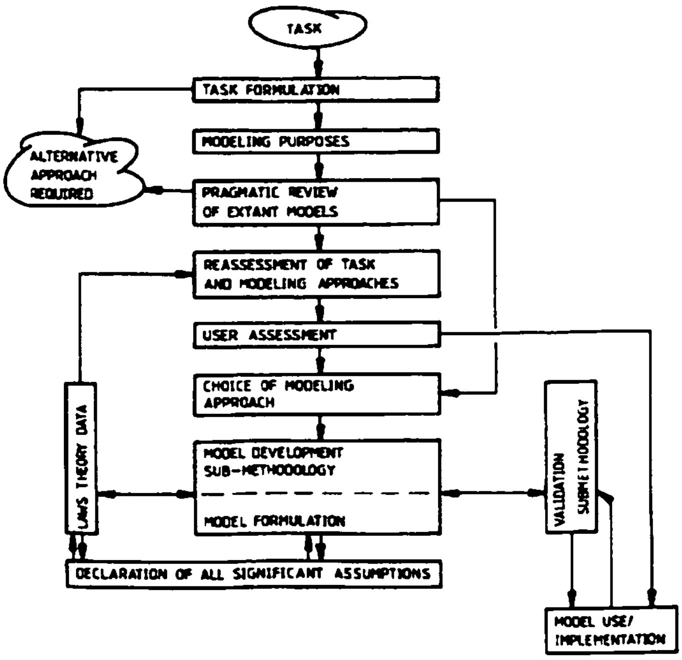


A systems diagram showing the five basic components that are of primary interest in modeling ecosystems.

Figure 1.5.2. (Adapted from Odum 1989)

The Modeling Process

While there probably are many different descriptions of the modeling process most are very similar in concept, differing only in nomenclature (Jorgensen 1997). The process described here is influenced by the author's experience (McCormick 1986), and reading Jorgensen (1997) and Botkin (1993), but follows the general outline (Figure 1.5.3) and nomenclature of Flood and Carson (1993). The idea to develop a model usually stems from a perceived need to accomplish a task. *Task formulation* itemizes the formal objectives of the perceived task,



A methodology for modeling structured systems.

Figure 1.5.3. (Adapted from Flood and Carson 1993)

and may point out that developing a model is not the most appropriate approach to meeting those objectives. If task formulation results in a decision to proceed with model development, the *modeling purpose* is then defined. The purpose of a model is to produce descriptive, predictive or explanatory outputs. Descriptive outputs are simple, concise metrics of system properties and are the least informative of the three. Explanatory output shows the interdependency of system behavior and structure and is very powerful in understanding the total system. Prediction is intermediate between description and explanation and shows how state variables respond to a change in an external stimulus.

Previous sections of this proposal introduced the perceived task and purpose for developing a meso-scale fire model. The model should predict fire spread patterns and also offer some explanation of the interaction between forcing functions (climate and topography) and state variable (fuel) in producing the resulting pattern. The following sections discuss the next steps of the modeling process described by Flood and Carson (1993), namely review of extant models, choice of modeling approach, model formulation and development, validation and evaluation. Theory and data are woven into the overall discussion, along with underlying assumptions and projected model uses.

Modeling Approaches

Verbal/sentential, diagrammatic, mathematical, statistical and logical are all methods of modeling, each having a particular type, methodology and use (Flood and Carson 1993). We use verbal/sentential models every day to convey thoughts and ideas to others through the structures of grammar and syntax. Conveying ideas through the use of diagrams is pervasive in human culture. A single diagram of Napoleon Bonaparte's march toward Moscow (Tufte 1983) tells the story of pursuit, battle and loss more efficiently and effectively than any series of books could. Pictures are more easily processed by the human brain because they allow parallel processing rather than the serial nature of sentential methods (Flood and Carson 1993).

Logical methods of model construction can incorporate Boolean logic, decision trees or expert knowledge for use in medical diagnostics and decision making. Statistical models typically try to predict future system conditions based on time-series or state-space data using regression, correlation or state transition probabilities (Markov chains). Mathematical methods are what most people think of when the term model is used, and these models are used to simulate material systems and predict system states.

It is entirely possible that Boolean logic and regression equations would be contained within a mathematical model. so there is no reason to assume exclusivity when considering these modeling methodologies. Rather, they are convenient ways of looking at the primary approaches one may take in researching and developing a model. This document reflects this in the use of sentential descriptions of fire. fuel and weather interactions. and diagrammatical representations of ecosystem functions and the fire intensity/fuel relationship. Later chapters describe the mathematical equations and assumptions of ANNs and statistical models used to evaluate performance.

Most modeling approaches theorize about and select environmental parameters based on observations and expert knowledge. Parameters are calibrated using reasonable assumptions and probabilities to incorporate processes that are well understood or easily encoded. Some models. such as FORET (Shugart and West 1977). use less direct parameter estimates and less reasonable assumptions. others. such as SORTIE (Pacala. Canham and Silander 1993). use more. Once calibrated. parameters were traditionally dealt with as constants in models. This fixes the scale over which the model is valid and limits the predictive resolution. All parameters have some range of values over which they vary. On average. working models behave as expected and give solid. average results. Models often fail to predict larger events because those events lie outside the averaged model parameter values when the process is initiated by a low-probability, but ecologically possible. alignment of environmental conditions. Fixed-scale models are often inflexible. only valid within a narrow state space. Inadequate responses occur when conditions within the modeled system switch from lower-level, endogenous process control to being controlled by upper-level, exogenous constraints.

Fire - Combustion and Propagation

The fire fundamentals triangle (Figure 1.5.4) contains three elements essential for sustained combustion: fuel, oxygen and heat (Agee 1993; Pyne, Andrews and Laven 1996). Combustion proceeds through three phases, ignition, propagation, and extinction (Clarke, Brass and Riggan 1994). Given an initial heat source, be it a spark from a passing train, a firebrand carried downwind, or a lightning strike, fuel moisture is the limiting factor for fire ignition. The moisture content of a particular piece of fuel is influenced by species, physical size, relative humidity, and time since last precipitation. Fine fuels, with a high surface area to volume ratio (e.g., twigs, leaf litter, grasses), are easily ignited and burn faster and with higher intensity than more coarse fuels. The moving front of a fire is typified by high intensity flames of short duration as fine fuels are burned. Coarser fuels can continue to burn for some time after the flaming front has passed, but with a lower intensity (Clarke, Brass and Riggan 1994; Pyne, Andrews and Laven 1996).

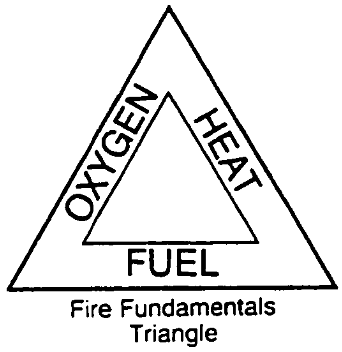


Figure 1.5.4. (Adapted from Pyne, et al. 1994)

Once sustained ignition occurs, elements of the fire environment triangle (Figure 1.5.5) become the controlling factors of the second phase of combustion, fire propagation (Countryman 1972; Pyne, Andrews and Laven 1996). Fuel moisture content is a function of short-term weather variables such as precipitation and relative humidity. Relative humidity varies with time of day, cloud cover, wind speed, season, and covertype percentage.

Topography can concentrate winds, and wind adds oxygen to the fire, increasing fire intensity and rate of spread. Positive slopes place unburned fuels physically closer to the heat and flames, also increasing rate of spread and intensity. Topographic aspect will also affect temperature (preheating fuels), relative humidity and fuel moisture. South-facing slopes generally are warmer and drier than north-facing slopes, so fuels on southern exposures will be warmer and drier and burn more easily.

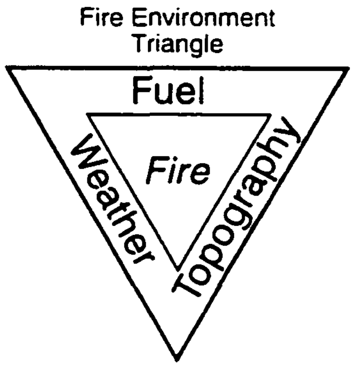


Figure 1.5.5. (Adapted from Pyne, et al. 1994)

Fire extinction, the third phase of combustion, occurs upon removal of one of the three fire fundamentals triangle elements. Natural or artificial fire breaks (e.g., roads, rivers, plowed lines) constitute physical removal of fuel from the flaming front. Precipitation or changes in relative humidity raise fuel moisture levels, increasing the amount of heat needed for combustion to continue, and dirt or chemicals placed directly on fuels limits the amount of oxygen available for combustion. Removing one leg of the fire triangle leads to fire extinction and is the basic principle of all fire fighting techniques (Brown and Davis 1973).

Fire Intensity and Severity

Effects of fire on an ecosystem are ranked by the magnitude, frequency and size of the disturbance in relation to the vegetative stratum affected (Heinselman 1981; Pickett and White 1985). The magnitude of a fire relates to its intensity or severity (White and Pickett

1985; Agee 1993). Fire intensity, as a function of flame length, is very difficult to measure directly outside of a laboratory setting or low intensity surface fires in the field. Surface, understory and crown fires generally progress from low to high intensity and rate of spread with increasingly higher flame length and fuel consumption (Agee 1993). Fire severity is a subjective assessment of the observable effects of fire on vegetation, such as root damage, stem scarring, leaf scorching or mortality. Agee (1993) notes that since severity is a function of vegetation type, fires of similar intensity may rank very differently in severity.

Organic fuels typically stratify into three layers starting from mineral soil: *ground fuels*, including duff, roots, peat and muck; *surface fuels*, including leaf/needle litter, grass, forbs, shrubs, branches, stumps and downed logs; and *aerial fuels*, including foliage, branches, snags, and moss (Brown and Davis 1973). Low intensity fires will consume a portion of the ground and finer surface fuels. Moderate to high intensity fires can consume all of the duff layer (down to mineral soil) and most of the surface fuels. If *ladder fuels* (e.g., low branches, tall shrubs, lichens or moss) are present, fire can move into a tree crown (torching) and, under certain wind and tree density conditions, move between tree crowns independent of surface fuels (Pyne, Andrews and Laven 1996).

The ecological consequences of fire (severity) can be assessed using multiple organizational criteria; organism, community, population, landscape or ecosystem. Soil organic matter may be completely removed, damaging tree roots and eliminating forest floor species. The resulting bare mineral soil may be vital for seed germination in certain species (Johnson 1992; Botkin 1993). Individual plants may be stressed or killed. Single stands or entire forests may be eliminated. Nutrients are lost through volatilization or soil leaching. Nutrients are also more available after a fire due to release from burned biomass and from reduced resource consumption. Removal of shrub and understory species by low intensity fires may benefit the dominant overstory species, such as red pine (Heinselman 1981). Periodically resetting stand succession by fire allows early-successional species to maintain a presence on the landscape (Holling, et al. 1995a).

Fire Regime

Fire regime, the pattern and variability in fire frequency and effects, can be defined by some combination of seasonality, severity, intensity, frequency, size or effect (Sapsis and Martin 1993). Pattern affects process, and, in turn, process affects pattern (Watt 1947; Pickett and White 1985; Turner 1989). Fire alters the condition and arrangement of abiotic and biotic elements on a landscape, and species respond to the changed environment. The type of vegetation that returns after a fire in part determines when fire will return and how severe its effects will be. This positive feedback loop between species and fire can develop into a relatively stable system over time, assuming that large scale climate (the upper-level constraint, the attractor) remains constant.

Over a large spatial and temporal extent and during a period of low climate variability, regular and periodic disturbances may create an equilibrium landscape with patches of forest exhibiting certain size and age class distributions. The climatic climax forest was predominant in the Lake States prior to European settlement (Mladenoff and Pastor 1993;

Heinselman 1981). The mean forest patch age class would approximate the mean return interval (frequency) of fire to a given patch. Using various techniques, researchers have analyzed stand origins in relation to fire, windthrow and insect outbreak regimes of many forest types in the Great Lakes region (Cooper 1913; Maissurow 1941; Heinselman 1973; Baker 1989a; Frissell 1973; Swain 1978; Whitney 1986; Frelich and Lorimer 1991; Holling 1978). It makes intuitive sense to manage ecosystem disturbance within a regime to which species are adapted. But, therein lies the problem. The native tree species present in the Lake States today have been present in the region for millions of years (Stearns 1997). The forest communities present just prior to settlement developed over the last 10,000 years during several shifts in climate and fire regime (Clark 1989; Clark 1990; Stearns 1997). Mladenoff and Pastor (1993) graphically depict the sequence of forest community changes that have occurred in the northern hardwood and conifer region since European settlement. With shifting climate, human impacts and exotic invaders, present day fire regimes can not be readily known or hypothesized from historical data (Schoonmaker 1998). Management must decide what ecological effects they want to produce with fire, and determine an appropriate fire regime to meet those expectations (Pahl-Wostl 1998).

Rowe (1983) defined five life history mechanisms that plants use in response to different fire regimes. *Invaders* widely disperse propagules and occupy a site after disturbance (e.g., aspen and birch) while *evaders* have long-lived or protected propagules (e.g., serotinous cones of jack pine) that survive the fire in the soil or canopy. *Avoiders* are intolerant of fire and reoccupy a site later in successional stages (e.g., hemlock). *Resisters* are able to endure all but the most intense fires at some life stage (e.g., thick bark on older burr oak) and *endurers* may lose above-ground biomass during a fire but are adapted to resprout from roots or surviving stems (e.g., oaks and shrubs). In areas that experience a range of fire severities, a species may employ several of these strategies to survive (Rowe 1983). Fire suppression favors avoiders and results in densely stocked, late successional forests. Frequent, low severity fires favor resisters and result in open stands of older individuals. Shrub-dominated landscapes or areas with patches of even-aged stands typically have high severity fires, favoring invasive, evasive or enduring life-history traits (Agee 1993). These five strategies are in feedback with fire (as an endogenous process) and affect how often fire returns and how it is carried across the landscape by the vegetation. The key point is species are not the relevant entities with respect to fire regime, rather these strategy categories are (Parker and Pickett 1998).

Fire History

Agee (1996) discusses two basic methods of determining fire frequency. At a fixed point (which may actually include several trees) on a landscape, frequency can be measured by looking at the time interval between fires as reflected in tree ring scars. Determining frequency over a large spatial extent involves assessing stand age distributions and calculating the fire rotation time of an area, that is, the average time it takes for fire to burn all of the landscape (Heinselman 1973). The point method is usually limited to areas with low fire severity (where many trees survive the fires), while the area method is usually employed in regions of typically moderate to high severity fires, where stand age infers the year of a stand replacing fire (Agee 1996). By carefully analyzing point and area data. historic fire regimes can be determined (Johnson 1992).

Disturbance regime attributes (size, timing, spatial distribution) can be represented statistically as frequency or probability density distributions (Baker 1992). Fire history data have been fitted empirically to the Weibull and negative exponential models (Johnson and Van Wagner 1985). A Weibull distribution models the relationship between the landscape age-class and fire interval distributions (Johnson and Van Wagner 1985; Baker 1989a).

The Weibull has shape and scale parameters (Figure 1.5.6) that make the distribution curve flexible and well suited to modeling the variable shape of fire interval data (Clark 1989; Baker 1989a). If the Weibull shape parameter (c) value is less than one, fire hazard is assumed to decrease as stand age increases; greater than one, fire hazard increases with age. The negative exponential is actually a special case of the Weibull where the shape parameter equals one (Clark 1989; Johnson

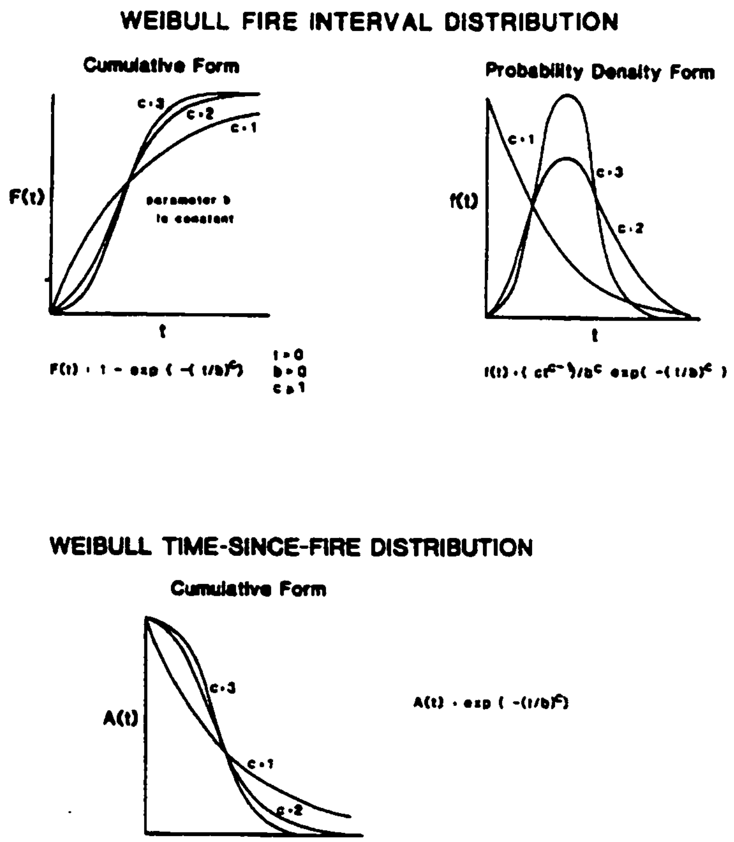


Figure 1.5.6. (Adapted from Johnson 1992)

1992; Baker 1989a). The negative exponential assumes that fire hazard is constant, i.e. that the probability of a stand burning does not increase with age. Van Wagner (1983) fit Heinselman's (1973) Boundary Waters Canoe Area (BWCA) fire data to the negative exponential, reducing Heinselman's proposed 100-year fire rotation estimate to 50 years (Heinselman 1981). In contrast, Baker (1989a) showed that the original BWCA data did not fit the negative exponential, but they did fit the Weibull with shape parameters greater than one. By clustering the data, Baker (1989a) found that different regions in the BWCA had different Weibull parameter values and fire interval distributions.

Equilibrium Concept of Landscapes

While the mechanics of fire incorporation in ecosystems are hard to observe directly or reconstruct from the past, the process of entraining exogenous perturbations into endogenous processes most probably shaped the forest communities and landscape patch mosaic present at the time of European settlement. Whether from lightning strikes or aboriginal peoples, wildfires on susceptible Lakes States landscapes selectively filtered the flora and fauna to the point where fire was integral to the long-term survival of many species. The spatial extent of a disturbance and the length of time between disturbances (i.e., regime) are recurring themes in any discussion of equilibrium.

There are at least three categories into which we could place a landscape suspected of being in equilibrium (Turner, et al. 1993). The first, *shifting mosaic steady-state* (Bormann and Likens 1979), assumes that, over a relatively long time span, the cover type of a particular patch may at any time change (shifting mosaic) but, when averaged over the entire landscape extent and the entire time span, the relative percentage of each cover type does not change (steady-state). In the second category, referred to as *stationary process with random perturbation* (Loucks 1970), random frequency of disturbance keeps the landscape mosaic from appearing stable at any point in time but since the communities respond by following the same successional vector after each disturbance the landscape is in equilibrium with respect to the process. The third, *stochastic or relative constancy through time* (Botkin and Sobel 1975), allows for variation in the landscape through time as long as any changes stay within the range of specified boundary conditions.

Baker (1989b) describes a 141-year segment (1727-1868) of the fire history in the boreal forests of the Boundary Waters Canoe Area (BWCA). He analyzed patch age class structure through time for stability. He concluded that the system was not in equilibrium with fire as defined by constancy or the shifting mosaic steady-state model over the largest area. This was primarily due to heterogeneous abiotic elements in the landscape and heterogeneity in the fire ignition pattern that greatly limited the occurrence of fire in certain areas. In smaller landscape units with a more homogeneous abiotic composition he felt there was equilibrium at certain scales, but this was due more to random chance in fire ignition than any underlying pattern.

Frelich and Lorimer (1991) looked for vegetative equilibrium with the dominant disturbance process (windthrow) in three forest preserves of different spatial extents. From the data presented and discussed, all three areas experienced small to moderate windthrow disturbances on an annual basis from thunderstorms (with low annual variation in number and severity of storms). While fire did occur in the areas studied, it did not significantly affect the overall vegetative pattern. Frelich and Lorimer's primary evaluation criterion was residence time of a tree in the canopy. New tree fall gaps accounted for less than 15% of any area studied for any given decade (i.e., a constant rate of disturbance through time). They concluded that the two largest preserves could be in a state of equilibrium with respect to windthrow based on the shifting mosaic steady-state hypothesis.

Juxtaposing the results of these two studies with the results of Davis and Botkin (1985) points to a fundamental problem in defining an equilibrium landscape. Baker and Frelich and Lorimer were seeking to prove or disprove equilibrium on landscapes based on analyses of a primary disturbance force (fire and windthrow, respectively). Davis and Botkin's results indicate that climate changes prior to and during the period of those two studies may have influenced the composition of those communities. For Baker, the 141-year time frame for analyzing fire occurrence coincided with the end of the Little Ice Age. Frelich and Lorimer looked at gap creation during the period from 1850 to 1969, showing a relatively greater percentage of gaps occurring in the two decade period from 1890 to 1910.

Davis and Botkin discuss a slight warming trend beginning in 1880 and ending in 1940. A most interesting observation from Davis and Botkin is that cool-temperate forests are still responding to climate changes of 200 years ago, and may continue to do so for another 100 years (i.e., our forests are not in equilibrium with respect to long-term climate). All three studies show that limitations in historical data can influence the resulting presumptions of stable regime and equilibrium landscape, as can limiting the time frame, data grain or extent of the area studied (Turner, et al. 1993).

Assumptions Underlying Regime and Equilibrium Models

A primary assumption in using the Weibull model in fire history analyses is that the largest fires on record should burn a relatively small proportion of the landscape in comparison to the total area under study (Johnson and Van Wagner 1985). For the BWCA data, Baker (1989a) found this assumption violated and suggests that the Weibull model is not valid for use in the BWCA. Considering the size and relative homogeneity of the BWCA, Baker's findings should be given serious consideration when assessing the results of fire regime studies in the rest of the Great Lakes region. Clark (1989) discusses other assumptions implicit in using probability distributions in regime analyses. Two primary assumptions are "environmental stationarity" and "constant hazard." Stationarity assumes that disturbance intervals are independent and come from the same distribution. Environmental stationarity is violated when the observed intervals between disturbances are dependant on the time frame in which the disturbance process is observed. Constant hazard implies that the probability of disturbance is constant, i.e. it does not change with time following a disturbance. Using 750 years of fire data from a 1-km^2 area in Minnesota, Clark (1989) shows how environmental changes on decadal and century time scales alter the fire regime and violate the underlying assumptions of regime calculations from spatial data.

The scale of the underlying disturbance regime(s) and the physical space on the landscape required for disturbance processes to occur are important factors to consider when developing any meso-scale model of fire. Equilibrium descriptions can be concerned with simple persistence through time of the ecological entity of interest (stochastic constancy through time). At another scale, always having a similar distribution of types, sizes or ages of an organism or community would be defined as equilibrium (shifting mosaic steady-state).

In essence, equilibrium is only a model pertaining to organization and scale. The model applies generally to concepts of organization in the material system through resilience (Holling 1986) and dynamic trajectory (O'Neill, et al. 1986). Equilibrium can be applied specifically when temporal and spatial scales are explicitly defined. Within the over-riding framework of disturbance, a determination of equilibrium can be made for a single species (population), an associations of species (community), the patch pattern and disturbance processes that created the pattern (landscape), or the flow of nutrients (ecosystem). So we find that, for the same material system, equilibrium can be defined differently depending on the ecological criterion specified.

Review of Extant Fire Models

We model fire primarily to better manage fire and its effects on ecosystems, communities and landscapes. Some fire models are stand alone while others are modules within larger land cover dynamics models. Extant fire models operate at many scales, use different predictive equations, and produce numbers or maps representing fire frequency, severity, spread rate, burn pattern or risk. The perceived need for the meso-scale fire model proposed here has several foundational reasons. Many fire models were originally developed for use in conifer-dominated forests of the western U.S. However, ecosystem differences (e.g., wind/elevation interactions, landform and cover type characteristics, etc.) may make these model structures inappropriate for the Great Lakes ecoregion. Wildfire modules within larger forest succession models, e.g., LANDIS (Mladenoff, et al. 1996), generally lack the resolution required for most forest-level management and planning efforts. Greater human presence on and around forested lands in the region (Figure 1.5.7) increases the potential for conflicting land management scenarios (Plevel 1997). Forest

Figure 1.5.7. Increasing density and presence of seasonal human habitation in the northern Lake States region places people not fully cognizant of land management requirements inside fire regulated forest communities and greatly limits management options with respect to fire.

land managers recognize the need for a wildfire model specifically applicable to the northern Great Lakes ecoregion.

Pioneering Fire Studies

Maissurow (1941) conducted one of the earliest studies of fire regime in the Lakes States, focusing on the northern portion of the Nicolet National Forest in Wisconsin and adjacent lands in the Upper Peninsula of Michigan. He concluded that 95% of the forests studied originated following fire disturbance. While using terminology more common for the time (forests were of poor quality, decadent, or silviculturally worthless), Maissurow's conclusions pre-date many of the "new" theories of ecosystem and community ecology. He points to fire as a necessary agent in the perpetuation of many species and notes that fire determines forest composition. The idea of local accidents determining forest composition rather than environmental determinism comes out in his conclusion about uneven-age hardwood stands occupying similar sites as even-aged stands of intolerant species; "This peculiar association of two groups of trees...explain the failure of all attempts by foresters to establish definite relationship between soil types and composition." Further, catastrophe curves, basins of attraction and Holling's four-box model appear in his observation that not all fires resulted in the restocking of a forest. High intensity fires often created grass and shrub dominated "subclimaxes and understocked, open and silviculturally worthless stands." Maissurrow's closing statement that fire has been and is "a normal, beneficial and necessary factor" in forest composition is echoed by most forest ecologists today.

One of the early quantitative studies of fire fundamentals and fire behavior was conducted by Fons (1946) in California. Having an engineering background, he approached the understanding of fire from a physical and chemical viewpoint. Initial field studies of fire had too many uncontrollable factors, so Fons moved into a wind tunnel and created fuel beds of uniform materials and known densities. From fires started in these test beds he developed equations and relationships based on eight fundamental variables. In essence, he considered fire spread to be the result of ignitions of fuel particles from adjacent burning fuel particles. His equations model the spread of fire as sequential ignitions through time. The eight fundamental variables controlling successive ignitions are difficult or impossible to measure in the field. Relationships were developed showing how those variables typically measured in the field influenced the fundamental variables and ultimately the rate of spread of a fire.

Behavior Models

Fons' engineering approach to fire modeling has remained predominant in the field. The majority of fire models in use today are based on fire spread relationships developed by Rothermel (1972) in the U.S., Van Wagner (Van Wagner 1969) in Canada, and McArthur (1966) in Australia, as reported in Baines (1990). Fire geometry models were proposed by Anderson (1983), Van Wagner (1969), and French, et al. (1990). Much work has been done to improve upon (Rothermel 1983; Andrews 1986; Rothermel 1993; Beer 1993) and implement (Rothermel 1991; Vasconcelos and Guertin 1992; Catchpole, Catchpole and Rothermel 1993; Xu and Lathrop 1993; Bessie and Johnson 1995; Finney 1996) Rothermel's original equations. McArthur's (1966) original fire spread rules were converted to equations by Noble et al. (1980) as reported in Baines (1990), and have been field tested (Baines 1990; Marsden-Smedley and Catchpole 1995).

Rothermel's equations require a description of fuel which includes depth, loading, percentage of dead fuel, moisture of extinction, heat content, surface area to volume ratio, mineral content, silica content, and particle density (Marsden-Smedley and Catchpole 1995). Required environmental variables include wind speed at half-flame height, slope and fuel moisture content (live and dead). Models based on Rothermel's equations perform adequately in predicting the fine detail of fire physics and chemistry, but often give simple treatment to the climatological and geographic aspects of fire spread. Rothermel's equations are only valid for surface fires.

Anderson's equations for determining the shape of a fire are limited to uniform fuels, uniform slope and uniform wind speed, conditions rarely available in nature (Clarke, Brass and Riggan 1994). To compensate for certain of these limitations Finney (1996) used 17th Century Dutch mathematician Christian Huygens' principle of light wave propagation (French, Anderson and Catchpole 1990; Knight and Coleman 1993) in FARSITE to model movement of a vectorized fire front and better correct for the fire front shape at any given time step. Other variations on the elliptical fire spread model have been proposed (Wallace 1993; Richards and Bryce 1995).

Other Approaches to Modeling Fire

Other recently developed models have taken advantage of raster-based simulation concepts (e.g., cellular automata (CA) and nearest neighbor decision rules) to incorporate concepts of diffusion (Clarke, Brass and Riggan 1994), percolation (Green 1993), or contagion (Li and Apps 1996; Gardner, et al. 1996; Hargrove, et al. 2000) in spreading fire across a landscape. CA are an n-dimensional array of cells with values that represent the global state of a variable. Each cell is a computer and updates its state at each time step based on the state of its neighbors. This limitation to interactions only between immediate neighbors makes computerization of CA very easy, and the efficient processing is often used to model complex systems (Karafyllidis and Thanailakis 1997).

Most CA models of fire spread require some estimate of the burn potential for each cell prior to running the model. The probabilities are often stochastic in nature, and multiple runs are used to develop a map of fire risk. Cellular automata have been implemented in fire models using Rothermel's (or others) rate of spread (Ball and Guertin 1992; Karafyllidis and Thanailakis 1997), Huygens principle (French, Anderson and Catchpole 1990), nearest-neighbor movement rules (Bryant, et al. 1993; Ratz 1995) and invasive epidemic processes (Green, Tridgell and Gill 1990). Clarke et al. (1994) present a unique method of fire propagation in a CA. Nearest-neighbor rules are not used, instead "firelets" are allowed to move about the array consuming fuel. If the firelet goes a certain distance from its starting point or encounters no fuel, it stops and either spawns a new firelet or goes out. The idea of firelets is based on an assumption that fire boundaries are fractal in nature. Firelet actions are recursive and self-similar, presumably fractal processes that will create fractal forms.

Analysis of Extant Fire Modeling Approaches

All fire models reviewed to date look at fire spread from the standpoint of the flames, pushing the fire front along if fuels are available or wind is strong enough. Results from some fire spread models suggest that different, upper-level elements are controlling under varied environmental conditions (Green, Tridgell and Gill 1990; Gardner, et al. 1996). Through repeated simulations (cf. Monte Carlo approaches) these models can determine the degree to which a given landscape is connected (i.e., able to carry a fire), when it is above or below some critical threshold value (Green 1994; Turner, et al. 1989). Information on percolation thresholds is needed for fire management of present-day landscapes and should be incorporated into wildfire models. Indeed, Turner and Romme (1994) and others (Simard 1991; McKenzie, Peterson and Alvarado 1996) discuss the need for a link between fine-scale mechanistic and broad-scale probabilistic wildfire models. They point directly to the essential need to be able to determine when landscape pattern or fire-line thermodynamics provides the more important constraint on wildfire spread.

Most wildfire models in use today (Rothermel 1983; Andrews 1986; Finney 1993; Green, Tridgell and Gill 1990; Clarke, Brass and Riggan 1994; Hargrove, et al. 2000) operate by encoding endogenous fire processes (e.g., rate of spread, intensity, etc.). In the preceding discussion I have intentionally omitted mention of any specific model by name. Instead, I focused on the fundamental aspects of these models and sought the unifying principles that each attempts to use in prediction. While each fire model has different, specific input requirements, any model of wildfire will require, in general, fuel, weather, and topography data (Fons 1946). What is usually neglected in mechanistic models of wildfire is the overlying landscape structure and variable climate that serves as context for and constraint on disturbance processes (Allen and Hoekstra 1992; Holling, et al. 1996; Simard 1991).

The concept of regime is preeminent in ecological studies of fire-regulated ecosystems. The term regime speaks to order, regulation, power and control, and is thus a comfortable concept for land managers and modelers to work with. Fire regime and historical range of variation are powerful concepts for forest management, ecosystem assessment and system design (Swanson, et al. 1994; Allen and Hoekstra 1998). Analyses of regime, equilibrium, and successional dynamics have been limited in scope, and usually fixed in scale, often inappropriately mapping different factors at the same scale. Also, Rowe's types, not species, are better organizers for analysis of fire in ecosystems.

To avoid complicating detail, complex ecosystem models usually only incorporate two hierarchical levels (Holling 1995b). Incorporating fire regime into a model sets intermediate variables of fuel and weather as the lower-level context; the model then produces effects on forests with variation in climate (both, higher-level, slower acting variables). Alternatively, physically-based fire models code low-level, fast combustion processes and scale-up to stands and forests. Local anthropogenic alterations of the biosphere are now connecting globally (e.g., 2xCO_2, ozone depletion, global climate change), crossing scales and ecological disciplines. Human society is now acting on a scale and at a rate equivalent with ecosystems, and our models must start to include variables from more than two hierarchical levels. The difficulty to this point has been connecting processes that have operating rates of different orders of magnitude (Allen and Starr 1982). Computer encoding each process with it's own time step would be very complicated, and produce a very complex model. Also, while the details of a single process may be captured and encoded, the detail of the cross-scale interactions of two separate processes may not be known or knowable.

Standing at the Crossroads of Fire Scale and Fire Theory

Little substantive change in the general field of wildfire spread modeling has occurred. Most certainly, existing fire spread models have been refined or expanded, with additional modules providing expanded capabilities, such as the crown fire and spotting simulation segments of FARSITE (Finney 1999). There are even new approaches to the 50-year problem of measuring fuel properties for use in physically-based spread models (e.g., Balbi et al. 1999; Richards 1999}. Fire sub-processes in landscape simulation models continue to grow in complexity, though some still use physically-based models for fire spread (e.g., Urban, Acevedo and Garman 1999; Sessions, et al. 1999; Keane, Morgan and Running 1996). Others, Roberts and Betz (1999) for example, still rely on statistical estimates of regime (e.g., mean fire return interval) to set *a priori* probabilities of burn potential while using sophisticated fuel accumulation and contagion algorithms to spread fire across simulated landscapes. Also, while not yet published in Ecology, Chi-Ru Chang's recent Ph.D. thesis (Chang 1999) presents a clear, hierarchical regime model that address the multi-scale, multi-factor nature of fire on large landscapes. Any model that seeks to understand the interactions of landscape, humans, and disturbance processes can learn much from Chang's exploratory modeling efforts.

A classification of fire models can take almost any form. Weber (Weber 1991) used three classes based on the internal structure of the model. Crookston, et al. (1999) placed models in a matrix of interactions between two processes, while Gardner, et al. (1999) ordered models with respect to perspective taken and understanding gained. McKenzie, et al. (1996), present yet another approach to classifying fire models using theory and the range of associated operational scales. Throughout the previous discussion I have chosen the perspective that there are only two general approaches to modeling wildfire spread patterns: fine-scale mechanistic or broad-scale probabilistic. The crossroads mentioned at the beginning of this chapter relate to the terms scale and theory, and the modification of those terms with micro, meso and macro. Mechanistic approaches (micro-theory) scale locally (micro-scale) to what keeps a fire burning. Fire spread in probabilistic models (macro-theory) is constrained by the rate of percolation across the landscape (macro-scale). Additions, refinements and modifications to existing models continue in an effort to address fire and it's effects at different scales, but the theoretical basis remains the same. Ostensibly meso-scale models use micro-theory models for prediction (e.g., FIREMAP and FIRE-BGC), or macro-theoretical relationships for determining fire extent (e.g., DISPATCH and VAFS/LANDSIM).

Baker (Baker 1999) presents a frank discussion on our lack of fundamental knowledge of the depth and complexity of most disturbances, despite the plethora of disturbance models. He points out limitations inherent in grid and vector-based fire spread algorithms, and suggests the need for expanding our modeling efforts beyond current approaches and incorporating external factors as well as local considerations. The first chapter of this document arrives at the same conclusion, and the remaining chapters present one possible method to achieve this goal. The problem with micro-theory and macro-theory models is that they seek to understand the process of disturbance, not necessarily predict well where that disturbance will spread. The ANN-based model described here seeks a meso-theory of wildfire spread that will work at any scale of interest to ecologists.

2

Data and Artificial Neural Networks

Study Area

Figure 2.1 shows the Northern Great Lakes states (Michigan, Wisconsin and Minnesota) with proclamation boundaries for the eight national forests. Based on conversations with Forest Service fire management personnel and ecologists familiar with these forest, the initial search for fire data focused on the Hiawatha National Forest in the eastern portion of Upper Michigan, and the Huron National Forest (HNF) in northeastern Lower Michigan (subset, Figure 2.1).

Fire Boundary Data

Prior to 1998 fire boundary information on the Hiawatha and Huron forests was recorded only as a rough outline on a USGS quadrangle. Since 1998 the Forest Service has been collecting fire boundaries using differentially-corrected GPS data. Eleven fires greater than 10 acres in size occurred during the summers of 1998 and 1999 on the Huron, while only three occurred on the Hiawatha. For this study, fire boundary and final fire report data were collected on all 14 fires. The Huron fires ranged in size from 12 ac. to 840 ac (Figure 2.2). The size of two of the Hiawatha fires were two orders of magnitude smaller than the third (~20 ac. vs. ~2000 ac.), and they occurred on the western district of the forest, whereas the large fire occurred in the east. Compartment/stand data for the Hiawatha are not yet

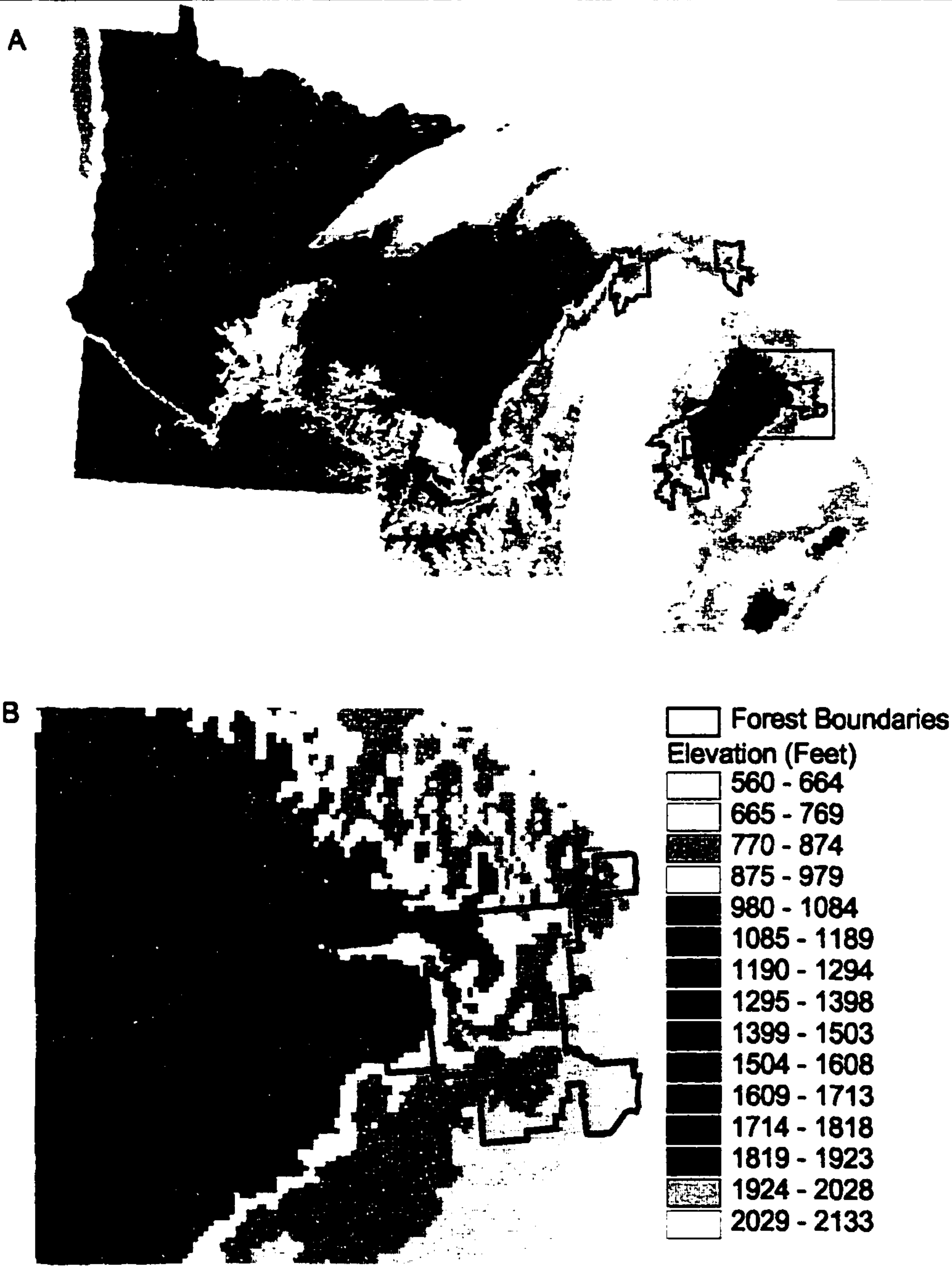


Figure 2.1: A - Northern Great Lakes States with national forest boundaries shown over elevation. Red box depicts approximate location of study site (B), the Huron National Forest in northern lower Michigan.

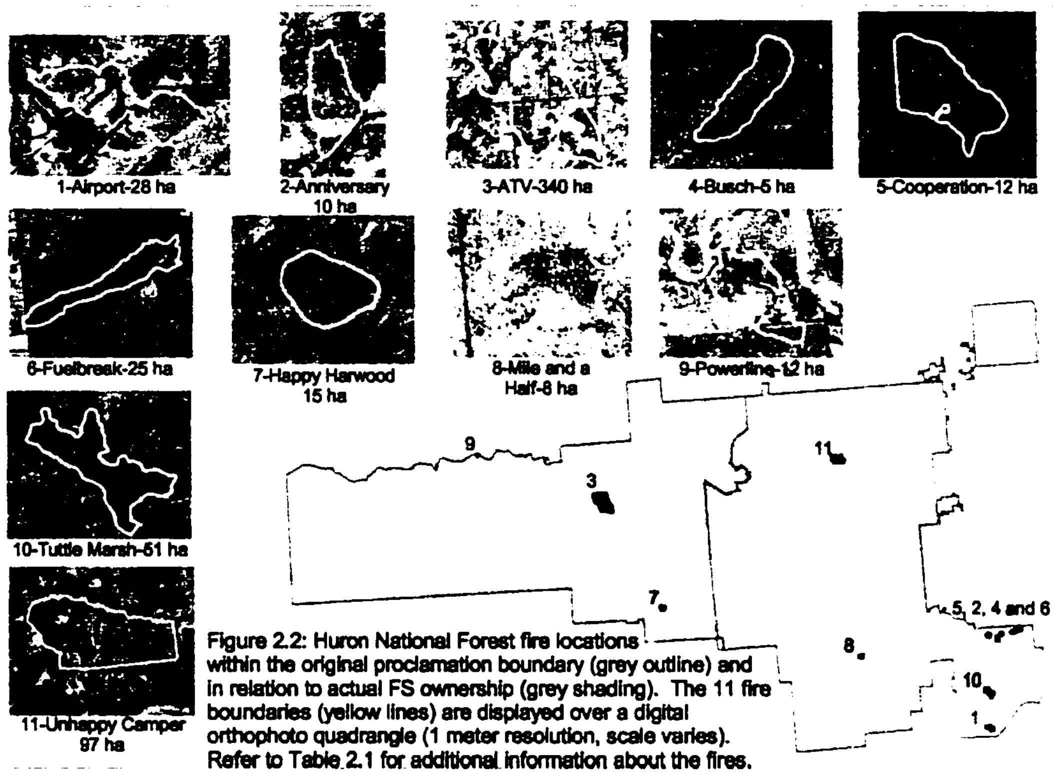


Figure 2.2: Huron National Forest fire locations within the original proclamation boundary (grey outline) and in relation to actual FS ownership (grey shading). The 11 fire boundaries (yellow lines) are displayed over a digital orthophoto quadrangle (1 meter resolution, scale varies). Refer to Table 2.1 for additional information about the fires.

available in electronic form. Because of the importance placed on these data, and in view of having only three fires of divergent size and spatial separation, no further analyses using the Hiawatha fires were conducted.

Environmental Variables

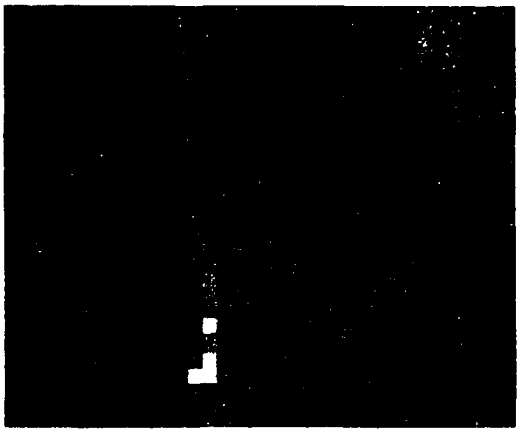
All readily available Forest Service digital data for the Huron National Forest ranger districts the fires occurred on were collected. Spatial data sets were converted to the modified Albers Equal Area Conic projection used by the GLEA. All coverages were displayed over a common base layer and checked for locational accuracy. Non-spatial data were sorted for each fire and checked for missing values. No changes to the coverages or text data were required as a result of this qualitative error analysis.

There exists a large range of variation in input variable values within a single fire and between fires, and this affects the degree of signal the ANN models get with respect to each input type. Figures 2.3a, 2.3b and 2.3c are graphical examples of some of these data. Using the Cooperation fire as an example, these figures show the primary ecological and environmental variables collected for the area surrounding each fire. These include:

Landsat Thematic Mapper (30 m resolution grid converted to a 10 m grid): Archived by North Central Forest Experiment Station. Two dates were available for Path 21/Row 29: 10 May 1993 and 25 August 1991.

DEM (USGS 7.5 minute (30 meter XY resolution) elevation data resampled to 10 meter grid): Digital elevation model downloaded from the USGS and complied by the Great Lakes Ecological Assessment (http://econ.usfs.msu.edu/gla/index.htm). The geographic position of the ATV, Powerline and Happy Hardwood fires is much different than any of the others, as reflected in the number and range of values as well as graphically in Figure 2.1 and 2.2.

Landsat TM Path 21/Row 29
10 May 1993
Color composite, Bands 4, 5 and 7
30 m resolution grid resampled to
10 m grid
Scale 1:12500



Landsat TM Path 21/Row 29
25 August 1991
Color composite, Bands 4, 5 and 7
30 m resolution grid resampled to
10 m grid
Scale 1:12500

Elevation From 1:24000 DEM
30 m (XY) resolution grid resampled
to 10 meter grid
Scale 1:12500

Elevation (Feet)
630 - 632
633 - 635
636 - 638
639 - 640
641 - 643
644 - 646
647 - 649

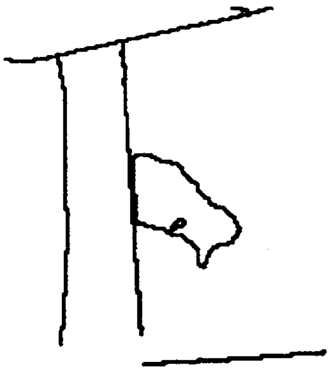
Figure 2.3a: Example data sets from the Cooperation fire. Similiar data were collected for all the fires shown in Figure 2.2.

Digital Orthophoto Quarter
Quadrangle 1997
Original 1 meter resolution
Scale 1:12500

45 - 61
62 - 77
78 - 93
94 - 109
110 - 125
126 - 141
142 - 157
158 - 173
174 - 189

Digital Orthophoto Quarter
Quadrangle 1997
1 meter resolution grid resampled to
10 meter resolution grid using
Neighborhood Mean in a 3x3 kernal
Scale 1:12500

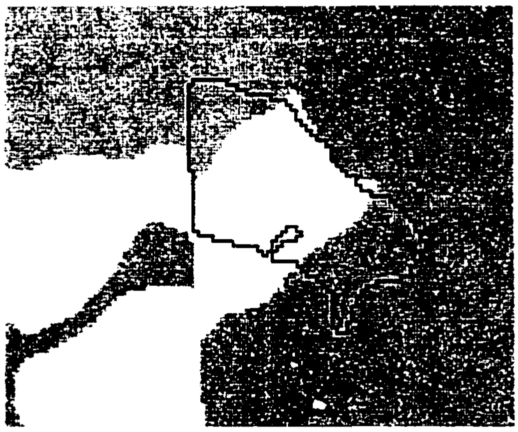
87 - 94
95 - 102
103 - 109
110 - 117
118 - 125
126 - 132
133 - 140
141 - 147
148 - 155
156 - 163

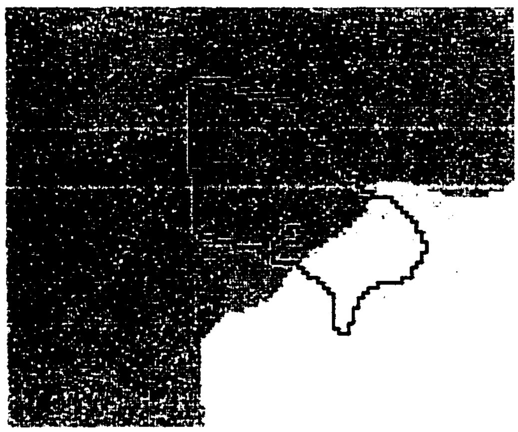


Forest roads from the HNF-CFF database
Converted to 10 meter grid
from original vector coverage
Scale 1:30000

-1 - No Data
103 - Secondary Highway
106 - Unimproved Road

Figure 2.3b: Example data sets from the Cooperation fire. Similiar data were collected for all the fires shown in Figure 2.2.





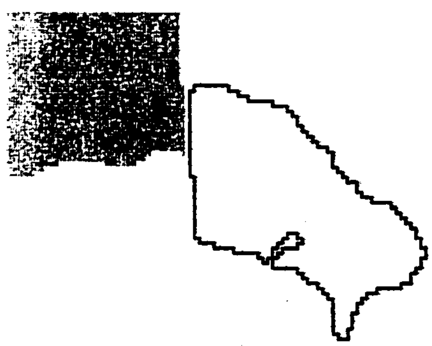


Figure 2.3c: Example data sets from the Cooperation fire. Similiar data were collected for all the fires shown in Figure 2.2.

Digital Orthophoto Quarter Quadrangle (DOQ) (1 meter resolution grid): Archived by North Central Forest Experiment Station. The photography was acquired over several dates in 1993 and 1994. A second grid was created using the Neighborhood Mean function in Arcview with a 3x3 kernal and a final output size of 10 m. This DOQ 10 m grid was used in ANN model development.

Rivers/Roads (vector coverage converted to a 10 m grid): Developed and maintained by HNF and other Forest Service personnel. Spatial accuracy for these data was good, but there were many errors of omission in the roads coverage (missing segments, entire roads). A code of -1 indicates no data (area other than roads or rivers).

Stand Type/Stocking Density/Year of Origin (Polygon coverage converted to a 10 m grid): Developed and maintained by HNF and other Forest Service personnel. Stand type and stocking density are the standard Forest Service cover type codes used for compartment/stand mapping purposes. Year of origin is the known year the stand was started (e.g.. following a clearcut or fire) or the estimated origin date for stands existing at the time of HNF creation. A code of 0 indicates no data. outside of HNF ownership.

Ownership (Polygon coverage converted to a 10 m grid): Developed and maintained by HNF and other Forest Service personnel. Depicts actual HNF ownership within the original proclamation boundary (Figure 2.2). A 0 code indicates Forest Service land. 999 indicates other ownership. The Airport fire started on HNF land but burned primarily on other lands; the Tuttle Marsh fire started and burned on HNF land. with only a small section on other lands; the Mile and a Half fire started on other lands and only slightly touched HNF land; and the Powerline fire did not involve any HNF land; all other fires occurred only on HNF land.

Ecological Landtype/Landtype Association (Polygon coverage converted to a 10 m grid): Polygon data developed and maintained by HNF and other Forest Service personnel. The ecological landtype (ELT) boundaries are from the initial ecoregion boundary delineation work done on the HNF. Subsequent refinement of the concept of ecoregions (Jim Jordan. draft) resulted in redefining the ELTs as landtype associations (LTAs). The ELT codes present in the database relate to the old LTA codes. and new LTA codes were developed for the forest. A code of -1 indicates no data. outside of HNF ownership.

Early Settlement Vegetation (Polygon coverage converted to a 10 m grid): Maintained by the GLEA. Data on land use/land cover in the mid-1800's as recorded in Government Land Office (GLO) survey notes. Polygon data compiled and digitized by Michigan Natural Features Inventory (Albert 1995).

AVHRR (1 km resolution grid resampled to a 10 m grid): Maintained by the GLEA. Data are from 1996 imagery collected for a nationwide land cover classification done by the USFS (Powell et al., 1993). Most fires have two cover types present, but only the Airport and ATV fires have a large portion of both types present within the fire boundary.

Climate Records: ASCII text files all recorded weather variables for the Mio Ranger District, Huron National Forest, weather stations were acquired for the period from 1995 to 1999. Also, 30-year monthly climatic averages for precipitation and minimum and maximum temperature were acquired from the GLEA.

Gridding or resampling processes did not change the original resolution of these data with the exception of the DOQ coverage. Altering the resolution of the 1 m DOQ to 10 m was not desirable from a data quality standpoint, but proved necessary for these initial trials to reduce the size of the input data vector and for ease of manipulating the pixel data via computer programs. Future modeling efforts should be conducted using the 1 m resolution data.

The primary significance of these data is that they were readily available to fire management personnel on any forest ranger district. As discussed in the original dissertation proposal and Chapter 1, a main tenet of this modeling effort was to use of data that did not require extraordinary effort to acquire (e.g., Keane et al. 1999) or intimate knowledge of fire models (e.g., the FARSITE model). While there were other data readily available, these particular variables were selected as representative of the three elements of the fire environment triangle (fuel, climate, and topography). The DEM data were of sufficient topographic resolution for this modeling effort, as were the Mio district weather station data for the climate leg of the fire environment triangle. The DOQ, TM, AVHRR and stand data provide information on fuel at multiple resolutions from multiple sources. The ownership layer was assumed to provide some indication of land management effort, which may directly or indirectly affect fuel and fire. The rivers and roads data were additional variables that would presumably affect the shape and spread of a fire. As seen in Figure 2.2, may fires burned along or up to road edges, and the Powerline and Tuttle Marsh fires skirted or were stopped by watercourses. Ecoregional coverages and, to some extent, the early settlement vegetation data integrators of climate, surficial geology, soil type, and potential vegetation data and may be useful indicators for predicting fire size and number.

Data Structuring

Fire records from the Huron National Forest consist of the fire start location and a GPS fire perimeter, along with administrative details such as start time, stop time, date, cause (human-related or other), personnel and the equipment used, and a cost analysis. No detailed information is kept on how far the fire travels in a certain time period, or where fire fighting activities were concentrated. At issue then is how to collect data on the fire's progression for use in training the ANN model. What is required is a *post hoc* rebuilding of a fire's progression from ignition point to its final shape.

As discussed in Chapter 1 fire is a contagion process, spreading outward from the start location. The fire shape is modified by wind speed and direction, topography, and fuel. Fuel and topography affect the final fire shape in a very specific and local manner, while wind speed and direction affect the fire shape in a general and universal manner. In general, fire spreads farther and faster downwind than it does upwind. This relationship is modified locally by fuel configuration in combination with topography. Bare ground and open water will not burn regardless of wind speed, and wind can concentrate and strengthen in canyons or weaken and disperse when crossing over ridges.

Using topography as the primary variable would still require some interaction with wind and fuel. Knowing that the adjacent pixel is 2 m lower or higher does not, by itself, indicate the fire will spread to that cell. It would matter greatly if the adjacent pixel represents the edge of a waterbody or was directly upwind of the currently burning pixel. Similarly, using primarily fuel would require wind and topography modifications. Wind speed and direction can be used alone with respect to ignition point in predicting fire shape. This presents the least ambiguous and most appropriate level of analysis for collecting these data *post hoc*.

Queuing Logic For Ordering Input Data

Input data for use in developing the ANN models were converted to a multi-band ERDAS LAN file for each fire. The first band contains the fire start location pixel, which has a value of one. All other pixel values for band 1 are set to zero. Band 2 again has only 0's and 1's, with the 1's representing the total area burned in the fire. Any number of additional bands can be present in the LAN file, each representing an environmental variable of interest. The output data vectors (i.e., the string of variable values) are stored in an ASCII file as comma-delimited text.

The queuing logic used for selecting and evaluating pixels *post hoc* reflect the theoretical work on fire growth modeling as summarized by Finney (1999). Fires with low wind speeds will grow in a more circular pattern; as wind speed increases the shape of the fire becomes more oval. Figure 2.4a shows the order in which the first 100 pixels are entered into the queue. This also represents the order in which pixels are evaluated by the ANN model. Starting from the fire ignition pixel (1), pixel queue order is determined by wind speed and direction. For example, as shown in Figure 2.4a, a fire with a wind speed of 5 and direction of Southeast has an initial queue of 15 pixels. From pixel 1 the fire front is expanded in the direction of the wind for a pixel distance of one less than the wind speed. Pixels that are adjacent to these downwind pixels (e.g., pixels 3 and 4 for pixel 2) are also added to the queue. This results in pixels 2 through 13 being added to the queue. Pixels representing the backing fire (14, 15 and 16) are then added to the queue to complete the first full loop of the queuing logic.

As each pixel is evaluated, additional pixels representing the fire front and backing fire at that pixel location are added to the queue. Hence, the next pixel in the queue (2) is evaluated in the same manner as pixel 1. As the four downwind pixels and their adjacent neighbors are selected, the queue is checked for duplicates. Since pixels 5 through 13 were entered into the queue during the first loop, only pixels 17, 18 and 19 are added from the evaluation of pixel 2's fire front. No additional pixels are added from evaluating pixel 2's backing fire because pixels 1, 3 and 4 are already in the queue. Pixel 3 is then evaluated in the same manner, and only pixels 20 through 24 are added as a result. The evaluation of pixel 4 results in the addition of pixels 25 through 29. The evaluation of the remaining pixels shown in light pink results in adding those pixels shown in purple for the fire front, and in yellow for the backing fire. The process continues, resulting in the pixels shown in gray and gold being added in the order indicated. Figure 2.4 shows the queuing order of the fire pixels a three different scales. Figure 2.4b shows further progression in evaluating pixels, with the region shown in Figure 2.4a now shown in light pink. Figure 2.4c shows all of the pixels evaluated for this particular fire, with the region depicted in Figure 2.4b shown again in light pink. The actual fire boundary is depicted by the dark black line in Figure 2.4c. The queue search limit, the outer gray line in Figure 2.4c, is determined by evaluating all pixels that are no more than two pixels outside the actual fire boundary (the black line in Figure 2.4c). For this particular fire, that results in evaluating six pixels beyond the actual fire front boundary and three pixels beyond the backing fire boundary. The edge boundary varies in size depending on the fire perimeter orientation.

To avoid searching the queue multiple times for duplicates, a record keeping image is created in a separate memory location. This output image has the same XY dimensions as the input file but only 2 bands. The coordinates of these two output image bands are used for tracking the pixels evaluated by the model (band 1) and the spread of the fire front (band 2). Every pixel in each band is initially set to zero. As a pixel is removed from the queue and evaluated the value for the same XY location is set to 1 in the first band of the output image. Thus, it is fast and efficient to check if a pixel is already queued. The second band of the output image is set to the same value as the second band of the input image as each pixel is evaluated. This creates a step-wise image of the actual fire burn pattern based on the order in which pixels are queued. This is a necessary step since there are no data on how the fires

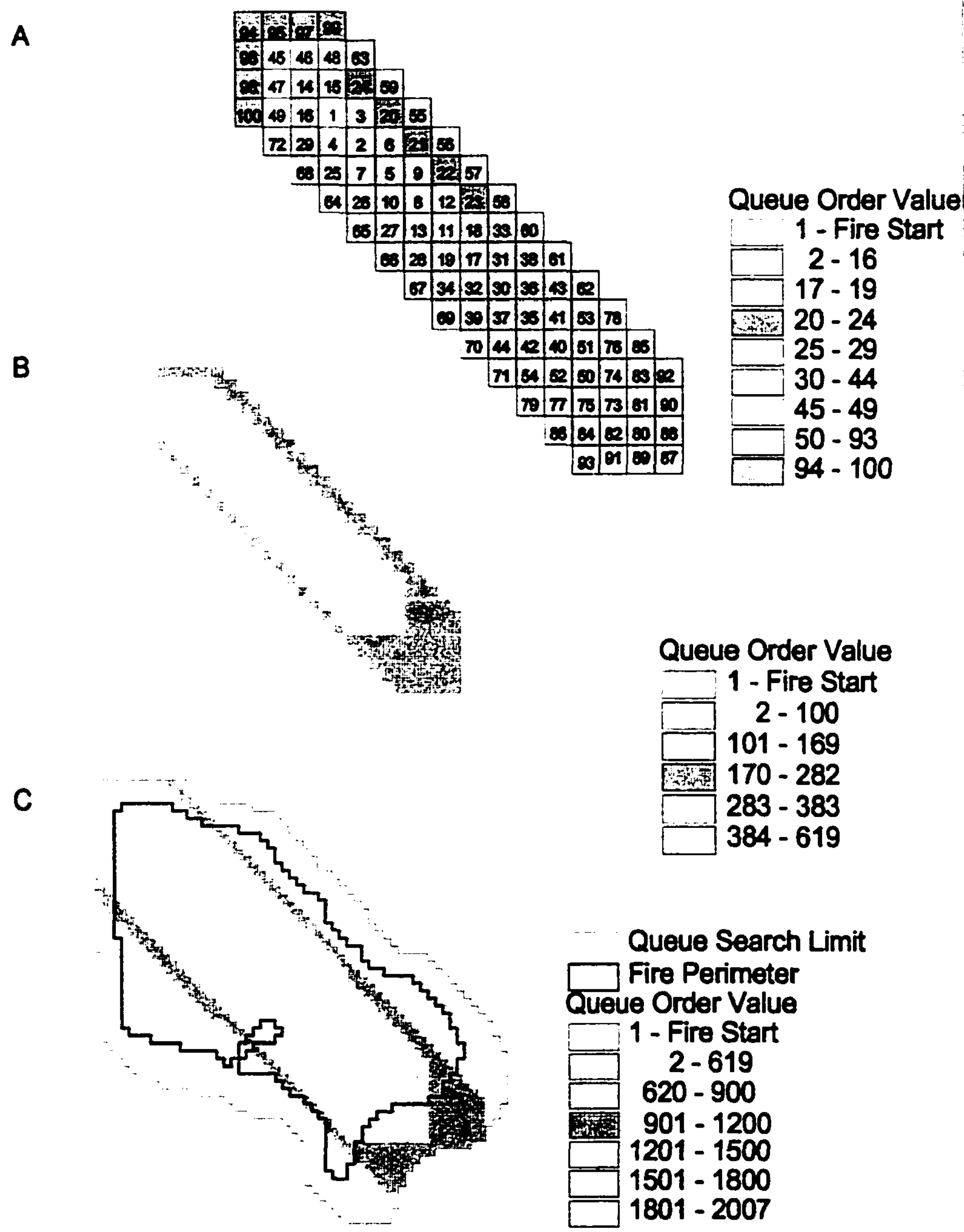


Figure 2.4. Graphical depiction of order pixels were queued (A - first 100; B - first 619; C - entire fire). The white pixel to the upper left of each image is the known fire start location. Each pixel represents 10 meters square. Refer to text for further discussion.

progressed across the landscape. The output image is saved as a 2 band LAN file for error checking and display purposes.

Selecting Other Environmental Variables

As a pixel is removed from the queue, the fire number, true XY coordinate, absolute XY coordinate relative to the fire start location, wind speed and wind direction are written to file. Next, the desired value, as represented by band 2 of the input image (i.e. a burn = 1, no burn = 0 code) is written to the output file, followed by the remaining environmental variables represented in the rest of the input bands. The environmental variables values for the eight surrounding pixels are also written to the file, with the current output image band 2 value being used to represent the fire front (burn status) at that time. Table 2.1 shows two sample data vectors resulting from the structuring and queuing process. Locational and environmental variable values for pixels 5 and 85 are shown along with the values for the eight neighboring pixels.

Figure 2.5 shows how the combination of input and output image values relate. For pixel 1,the fire start location, input band 2 would have a value of 1 (i.e. the desired value), but output image band 2 would have a value of 0 since it had not been evaluated yet, as is the case for the eight nearest neighbors (as shown in box A, Figure 2.5). Once pixel 1 is evaluated, band 1 of the output is set to 1 and band 2 is set to the value from the input band 2 (the actual burn status code). Pixel 2 is removed from the queue and evaluated, it's location and desired value as well as additional environmental variables are written to the output file.

Table 2.1 *Example input data vectors for pixels 5 and 85 of the Cooperation fire. See text for further discussion.*

Nearest Neighbor	True X	True Y	Absolute X	Absolute Y	Wind Speed	Wind Direction	Burn Status	DEM	DOQ 10 m	ELT	Owner	Roads	Rivers	Stand Type	Stand Density	Year of Origin	1993 TM 3	1993 TM 4	1993 TM 5	1993 TM 7	1991 TM 3	1991 TM 4	1991 TM 5	1991 TM 7
Pixel 5																								
X	63	71	2	2	5	7	1	643	131	2	0	-1	-1	53	5	1919	36	50	99	43	25	71	78	25
1			3	2	5	7	0	643	128	2	0	-1	-1	53	5	1919	36	50	99	43	25	71	78	25
2			1	2	5	7	0	643	133	2	0	-1	-1	53	5	1919	39	54	112	49	27	75	85	30
3			3	1	5	7	0	643	130	2	0	-1	-1	53	5	1919	36	51	96	41	27	68	78	28
4			3	3	5	7	0	643	128	2	0	-1	-1	53	5	1919	36	50	99	43	25	71	78	25
5			1	3	5	7	0	643	136	2	0	-1	-1	53	5	1919	39	54	112	49	27	75	85	30
6			1	1	5	7	1	643	129	2	0	-1	-1	53	5	1919	38	55	101	47	31	69	84	30
7			2	3	5	7	0	643	132	2	0	-1	-1	53	5	1919	36	50	99	43	25	71	78	25
8			2	1	5	7	0	643	130	2	0	-1	-1	53	5	1919	36	51	96	41	27	68	78	28
Pixel 85																								
X	72	77	11	8	5	7	1	643	119	2	0	-1	-1	0	3	1984	33	50	90	39	26	68	78	25
1			12	8	5	7	0	643	119	2	0	-1	-1	0	3	1984	33	50	90	39	26	68	78	25
2			10	8	5	7	1	643	119	2	0	-1	-1	0	3	1984	35	50	95	41	27	70	77	27
3			12	7	5	7	0	643	121	2	0	-1	-1	0	3	1984	34	51	90	40	26	68	80	27
4			12	9	5	7	0	643	116	2	0	-1	-1	0	3	1984	33	50	90	39	26	68	78	25
5			10	9	5	7	1	643	119	2	0	-1	-1	0	3	1984	35	50	95	41	27	70	77	27
6			10	7	5	7	1	643	120	2	0	-1	-1	0	3	1984	36	51	95	40	27	69	80	28
7			11	9	5	7	1	643	117	2	0	-1	-1	0	3	1984	33	50	90	39	26	68	78	25
8			11	7	5	7	0	643	122	2	0	-1	-1	0	3	1984	34	51	90	40	26	68	80	27

Neighbor	6	8	3
Pixel	2	X	1
Key	5	7	4

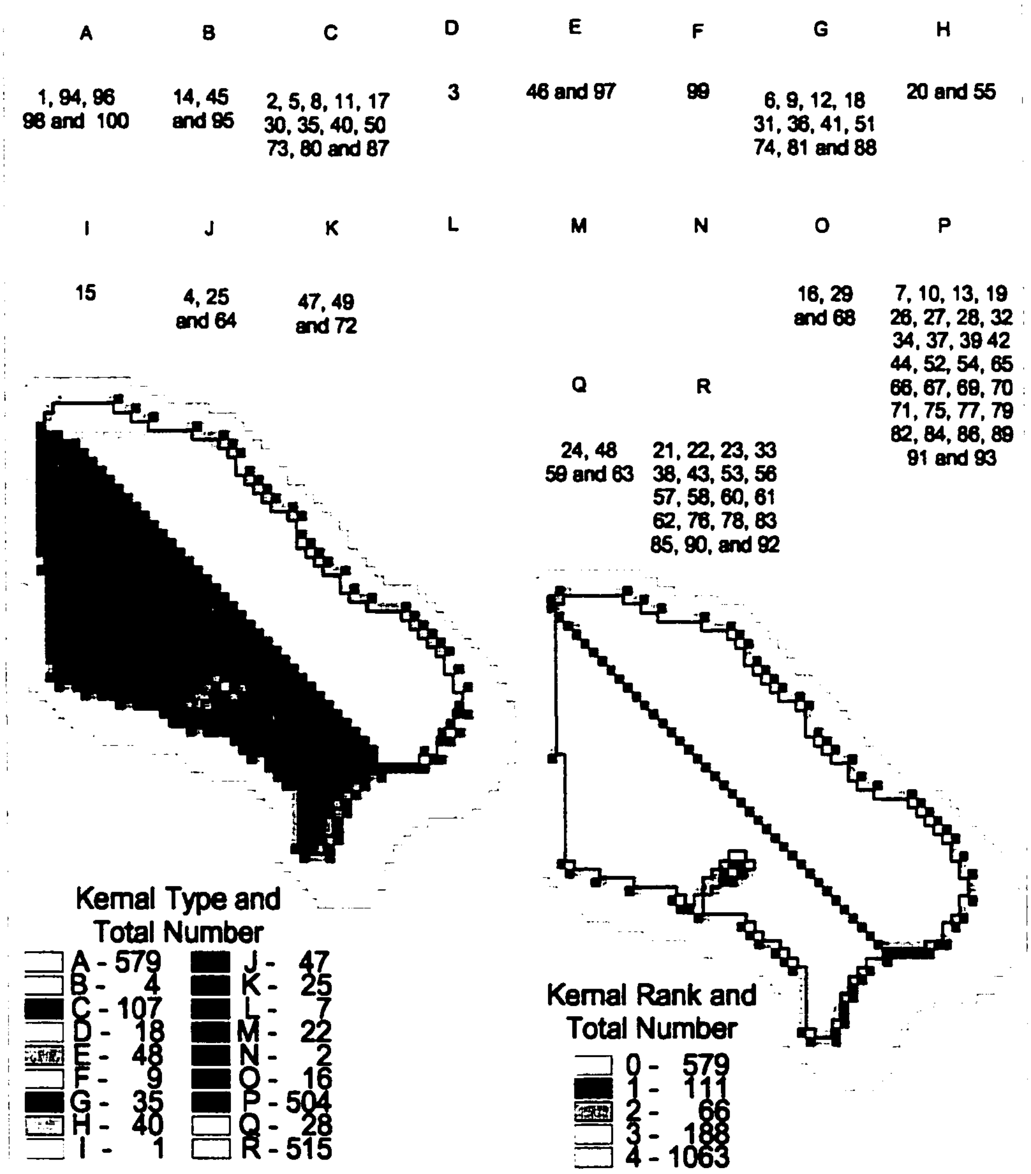


Figure 2.5. Nearest neighbor fire configurations (Boxes A - R) showing burned (grey) and unburned (green) pixels. Numbers below each box refer to the first 100 pixels shown in Figure 2.4. Kernal type map shows the fire configuration used for each pixel evaluated. The kernal rank map groups and orders the number of nearest neighbors that appeared as burned for each pixel evaluated. See text for additional discussion. Each pixel represents 10 meters square.

As shown in box C. Figure 2.5. the known configuration of the fire when evaluating pixel 2 is that only pixel 1 has burned (as reflected by the values contained in output image band 2). As pixel 3 is evaluated only the burn status of pixels 1 and 2 is known (box D. Figure 2.5).

The numbers listed below each of the boxes in Figure 2.5 represent the way the fire boundary looked for the first 100 pixels (Figure 2.4a) as they were evaluated. The map of the fire located on the left side of Figure 2.5 depicts which neighbor pixel fire status configuration (A - R) was used for each pixel evaluated by the model. The map on the right side of Figure 2.5 presents similar information but with the 18 box types condensed to five classes based on the number of burn pixels present (0. 1. 2. 3 or 4) in the neighbors adjacent to the pixel being evaluated. The black pixel on both fire maps represents the start location (pixel 1).

Table 2.2 lists date. time. size and ecoregion information for each fire along with the size of the total study coverage for each fire (total rows and columns), wind speed and direction. and fire start coordinates. The last five columns relate to the results from the data structuring/queuing process described above. Total pixels burned is the number of pixels inside the known fire boundaries as shown in Figure 2.2. and total pixels evaluated is the sum of the burned pixels and the pixels evaluated outside of the fire boundary (e.g.. as shown in Figure 2.4c). Stratified subsets of the fire data were created. as each fire was evaluated. based on the number of pixels evaluated at that point. Three subsets were created. using three IF-THEN statements. If the evaluation number was a multiple of 5. then it went into the Subset 1 file (resulting in 20% of the data being collected). If it was divisible by 3 but not by 5 then it went into the Subset 2 file (28% of the data). If it was not divisible by 3 or 5.

Table 2.2 *Data details for each fire on the Huron National Forest. See text for discussion.*

	Date	Time	Acres	Ecoregion	Total Rows	Total Columns	Wind Speed	Wind Direction	Fire Start Coordinates	Total Pixels Evaluated	Total Pixels Burned	Stratified Subset Totals: 52% of Pixels	Stratified Subset Totals: 28% of Pixels	Stratified Subset Totals: 20% of Pixels
Airport	07/23/98	1600	68	212Hr7	220	205	4	6	43/ 96	4166	2746	2222	1111	833
Anniversary	04/24/98	1730	26	212Hr1	92	72	3	9	32/ 22	1724	1046	920	460	344
ATV	05/01/99	1730	840	212Hq1&2	429	372	5	15	307/340	38177	34014	20362	10180	7635
Busch	09/06/98	1430	12	212Hr1	79	74	4	11	49/ 28	988	499	527	264	197
Cooperation	08/17/98	1200	30	212Hr1	186	148	5	7	61/ 69	2007	1216	1070	536	401
Fuelbreak	05/19/98	1700	62	212Hr1	227	216	7	4	43/141	4303	2514	2295	1148	860
Happy Hardwood	05/01/99	1500	38	212Hq3	148	142	3	15	91/ 82	2233	1574	1191	596	446
Mile and a Half	06/29/98	1600	20	212Hr1	97	76	8	5	16/ 50	2001	826	1067	534	400
Powerline	05/??/99	??	127	212Hq1	97	99	5	15	73/ 75*	2114	1212	1128	564	422
Tuttle Marsh	06/04/98	??	240	212Hr5	274	254	5	7	88/108	7518	5163	4010	2005	1503
Unhappy Camper	04/30/99	1500	30	212Hm1	223	248	5	15	210/134	11810	9665	6299	3149	2362

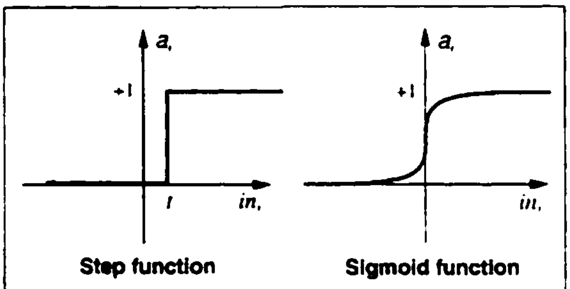
it went into the Subset 3 file (58% of the data). These subsets could then be combined to provide test data comprising either 20, 28, 48, 52, 72, 80 or 100 percent of the data for any given fire. This subset method evenly sampled across the range of variation within each fire, a necessary criterion for efficient and effective ANN model development.

A Primer on Artificial Neural Networks

As described in Chapter 1, conceptually neural networks are quite simple and can be represented as graphs composed of a series of linked nodes (Figure 1.1) that represent biological neurons and their connections. Multi-layered feed-forward networks (also known as MLPs, multi-layer perceptrons) are acyclic and have a series of nodes arranged in layers (input, hidden and output), with links between every node in adjacent layers (Figure 1.2). Full connectivity is not a requirement for a functioning neural network. There is typically only one input and one output layer. A network with one hidden layer can learn most continuous functions, while multiple hidden layers can learn discontinuous functions (Russel and Norvig 1995). Each link in the network has a numeric value (weight), the strength (value) of which relates to the local node's effect on the whole network. Input values are multiplied by the weights of the input links leading to each node in the hidden layer (Figure 1.1). Each node in the hidden and output layers performs two functions: a linear summation of the weighted inputs and then a nonlinear transformation of that sum using an activation function (Russel and Norvig 1995). The activation function produces an activation value for each hidden node that is "fed forward" to the output layer. The nodes of the output layer also calculate a weighted sum, and the activation function produces the output value.

Activation Functions, Thresholding and Bias

Figure 2.6 shows two types of activation functions; there are many more. For the step function, if the weighted sum (in_i, Figure 1.1) exceeds the threshold (t), then the node output (a_i, Figure 1.1) equals one, otherwise it is zero. This simulates the all-or-nothing response of a biological neuron. Most backpropagation learning rules require that the activation function be differentiable at all points, so a sigmoidal function, like the on shown in Figure 2.6, is typically used. Another type of sigmoidal function, Tanh, has an activation range from -1 to +1. Hidden and output nodes are generally referred to by the type of activation function used (e.g., sigmoidal nodes or Tanh nodes).



$$\text{step}_t(x) = \begin{cases} 1, & \text{if } x \geq t \\ 0, & \text{if } x < t \end{cases} \qquad \text{sigmoid}(x) = \frac{1}{1+e^{-x}}$$

Figure 2.6 (Adapted from Russel and Norvig 1995)

Learning in ANNs

There are two types of learning in neural networks, supervised and unsupervised. Unsupervised learning does not use target (output) data. The network analyzes input data and tries to reflect some aspects of those data in the output. Nodes compete to represent best the input vector. This usually results in a compression of the data characteristics and is comparable to statistical clustering techniques or other continuous data reductions, such as principle components analysis. For this study, fire burn patterns (target data) are available.

so supervised training of the ANN fire models is possible. There are several dozen supervised learning methods or algorithms. The most widely used is standard backpropagation of error, or backprop. The backprop algorithm is essentially a gradient descent search in weight space (Russel and Norvig 1995).

To measure the error of a network, an input data vector (e.g., the string of environmental variable values produced by the queuing program) is presented and the output is calculated. If the calculated output is the same as the target (desired) output, the error is zero and the weights are not changed. If there is a difference between the calculated and target outputs, the change in link weights between the output and hidden nodes is calculated as a function of the value of the weight, total error, learning rate, and output node activation function. The weights between the hidden and input nodes are similarly updated. Thus, the error at any output node is propagated back up through the network to the input nodes via the weights associated with each node and node type. Gradient descent will always find a local minimum but does not guarantee finding the global minimum of the error surface (Russel and Norvig 1995).

The propagated error can be further modified by altering the learning rate and adding a momentum term. Momentum "points" the search down-gradient by keeping track of the direction and size of weight changes and calculating a more optimal path along the error surface. Speeding the training process with learning rate and momentum terms still does not guarantee finding a global minimum. The original momentum learning rule always uses the same step size. Other momentum-like learning rules, like Quickprop or Delta-Bar-Delta, contain modifications to the momentum term. The learning rate initially can be set high and then slowly reduced to speed network training by making large changes to weight values during early training (big steps) then gradually smaller steps as a error surface minimum is approached. The early fast learning rate moves the system to the likely neighborhood of a global minimum. The slower rate then fine-tunes the analysis.

Optimal Network Size

Any number of nodes can be in each network layer. For a given input space/output space, there is an optimal hidden layer size that provides the best mapping between the two spaces using the fewest nodes. A trained ANN with too many hidden nodes will memorize (overfit) the training set, impairing its ability to generalize about new input data vectors. However, introduction of noise into the data can ameliorate the data memorization problem. Too few nodes will not learn all of the training data. Each node can be considered as learning the function that transforms the coordinates of a cluster of input data to the coordinates of the corresponding output data cluster.

There is no perfect way of determining the final configuration of a network, but two basic approaches are to start with few (or one) hidden nodes and add, or start with many and reduce. The tiling algorithm of Mezard and Nadal (1989, as described in Russel and Norvig 1995) is a formalization of the "start with one" method. The single hidden node will learn what portion of the training data set it can, then an additional node is added to learn those input vectors not mapped by the first node, and so on. The ANN that reads postal zip codes was developed by starting with an initially very large trained network. After the initial training, the number of network connections was reduced by selecting non-vital connections and setting those link weights to zero, a process called optimal brain damage (Le Cun, et al. 1989, as described in Russel and Norvig 1995). This cycle of retraining and brain damage was repeated several times, eventually eliminating 75% of the original connections and removing some hidden nodes completely while maintaining a high accuracy rate.

Verification and Validation and Training and Testing: A Rosetta Stone

Model verification can be thought of as "initial tests to ensure that the model can adequately reproduce the data used to build it" (Pearson et al. 1999), essentially a test of the model's internal logic (Jorgensen 1997) or structure. Often the term calibration is used to imply verification (Oreskes et al., 1994), though calibration is more appropriately associated with the process of altering parameter values (associated with the logical structures) such that model output values agree with the expected values (Jorgensen 1997), at an acceptable level of error. Calibration refers to the dynamic aspects of model construction, verification to the structural aspects of the process. The two are linked in a feedback process that results in a final working model. Only at this point is validation, the testing of model performance on an independent set of data (Pearson et al., 1999; Jorgensen 1997), appropriate.

As with almost any term used in science, definitions vary. Oreskes et al. (1994) present the philosophical argument that "verify" means to establish truth and "validate" means to establish legitimacy. Since all models are a simplification of the subject system (Ahl and

Allen 1996), they are by definition not true, and thus unverifiable in a restricted sense of the word. Similarly with validation, because ecological systems are open, model legitimacy is limited to the range of experiences of the modeler and the precision of data used in model construction. Still, just because a word has many definitions does not mean science should avoid use of the term altogether. Instead, science should embrace this definitional diversity and at the same time take responsibility for clearly defining what is meant by the given use of a term. Perhaps it is for this reason that the field of ANN modeling has avoided the terms verification and validation (Maier and Dandy, 2000), instead choosing to use training and testing, terms much less imbued with the heavy need to establish truth and legitimacy.

For the model development processes described in this document, the term training is equivalent to calibration and verification (i.e., parameter refinement and internal logic checking), and testing is equivalent to validation (i.e., a test using independent data). The data manipulation and training phase of ANN model development, as discussed in detail in Chapters 2 and 3, is in essence the combination of dynamic calibration and structural verification. Data are presented to the network and an output is produced. The difference between the output and desired value is compared (i.e., the model structure is evaluated). If the difference is unacceptable, the weights of the model are adjusted in a manner proportionate to the magnitude of the error (i.e., dynamic calibration of the model) and the process of data presentation, value comparison and weight adjustment is continued until an acceptable level of error is reached. The final ANN model is tested, using a completely independent data set, to see if it is valid (i.e., produces an output reflective of the known range of the test data). Poor performance during the testing phase does not mean that the model is invalid, it just means that the model does not recognize the training and testing data sets as coming from the same population (Maier and Dandy 2000). This may appear on the face of it to be a contradiction. However, if the model was over-trained then the trained network may be valid for the data on which it was trained while nevertheless recognizing the test data as coming from a different population, namely one on which it was not trained. The difficulty here is that the model is coherent only relative to a certain level of analysis. This is in contrast to, for example, building a simulation model, where there is a normative standard as to the level of analysis. Neural network analyses stand outside that narrative convention.

When a model does perform well during both the training and testing phases it is said to have generalized the relationships present in the training data set, and can interpolate between or extrapolate beyond those data when encountering independent data during testing. The term "validation" and "verification" are used often in simulation modeling, but turn up much less often in data reduction systems such as factor analysis. The reason is the levels of analysis issue raised above. ANNs are data reduction models, not simulation models.

3

ANN Model Development and Analysis

NeuroSolutions (NeuroDimension Inc.,Gainesville, FL, http://www.nd.com) was chosen as the program to use in developing the ANN models. This program was chosen over two other commercial neural network software programs for its many features, including the ability to construct modular networks and to produce C++ code of the final trained networks for use with other programs.

There is no single, cookbook approach to developing ANN models. The process is iterative, using informed human judgement in association with network response indicators. Indicators built into the NeuroSolutions interface include a simple graph of the mean squared error (MSE), presented as a cost value defined as MSE/2, for each training or testing epoch. One epoch is a complete presentation of all the input data vectors to the network once. Also, for this document, the term exemplar is synonymous with input data vector. Also, there are various calculated statistics, such as a confusion matrix, percent error, correlation coefficient (r), and two metrics (AIC and MDL) that use the MSE as a base and calculate a penalty based on the size of the network. Because each indicator is calculated in a different manner from the same data, any one indicators is usually insufficient to judge the quality of an ANN model. Also, the statistic and metric values alone are not very informative as to model performance; they are best used to compare predictions between models.

Stopping Criterion

Once training of a network begins the first set of exemplars are presented to the network. errors are calculated and weights updated. There has to be a method to stop the training effort at a point where sufficient training has occurred to predict accurately but not over-learn the training data lose generality. There are two main ways of doing this. Setting a limit on the number of epochs (e.g.. stopping at 1000 iterations) is one. and this is often done with a new data set to get a feel for how the network responds via the indicators. The second method is to set some stopping criterion based on the change in error between epochs. For example. if the difference in network error between two training runs was 0.05. and the stopping criterion was 0.1. then training would stop.

The stopping criterion can be used on only the training data. or on a second data set referred to as cross-validation (CV) data. A CV data set is usually a random subset of the input data and is not used to update network weights. It is only used to test the network response at the end of each epoch. Usually the stopping criterion when using CV data is set to detect an increase in error. The theory is. if the network is learning the training data it is also learning the CV data. since they are a subset. As the network trains it reaches a point where it starts to memorize the input data and loses the ability to accurately predict the CV data (it loses the ability to generalize). At that point. the CV error will go up, and training is stopped. As an example, Figure 3.1 shows a training run where no stopping criterion was set. The active cost graph reflects the training error. and the CV cost reflect the CV error. With a CV stopping criterion set. training would have stopped where the graph first flattened out (just before the small peak in the middle of the curve). As training continued, the training error continued to drop, but the CV error rose. Both stopping criterion methods were used in the development of ANN fire models described below.

The ANN Training Process

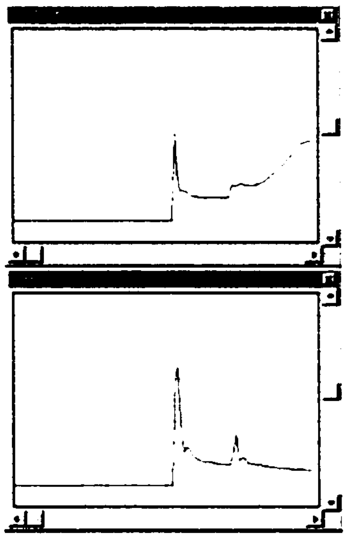


Figure 3.1 NeuroSolutions graph of training (active) and CV cost response.

Depending on the indicator responses, changing the number of hidden nodes, activation function type, learning rule, input data, or some combination of these, may be done to improve network performance. The process of network alteration in pursuit of a predictive network may appear on the surface to be more a drunken walk than a refined scientific investigation. In many cases it is a drunken walk, but one usually guided by the sure knowledge of how different node types affect output, how different learning rules work, and what sort of signal the network may be getting from the input data. The following description of network development for predicting wildfire spread at some point involves changing all of these networks aspects, and in an apparently non-rational manner. The point to focus on is not the thing in the network that is changed, but the resulting change in the networks predictive ability. In the end, it is not the network configuration that is vital, it is the ability to predict.

The active cost graph shown in Figure 3.2 is from an unsuccessful training trial. The network is presented with the training data and an error value is calculated. As learning occurs and the network weights are updated, the error value should gradually decrease. If there are sufficient nodes in the hidden layer, the error response curve will gradually approach zero. As seen from Figure 3.2, there are insufficient nodes to fully learn the relationship between the input variables and desired output value. The graph does not settle down to a smooth, descending curve. At this point, training would be stopped, the number of hidden nodes increased, the network reset (network weights re-randomized) and training started again.

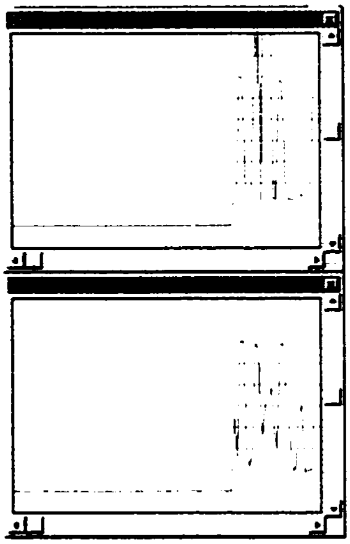


Figure 3.2 NeuroSolutions graph of training (active) and CV cost response.

Figure 3.3 shows a successful training session, with the CV and training data showing an initial high error value, then relatively smoothly decreasing to near zero (less than 0.1). At this point, when the absolute change in the CV error value does not change by a pre-set value (e.g., 0.04 percent per epoch), the training would automatically stop. If the final training r and percent error values (as shown in the large text box) are above 0.9 and below 10 percent, respectively, the test data and CV data are presented to the network. The results for these two data sets are shown in the bottom two sets of numbers in the performance measures text box. A value of greater then 0.85 for r and less than 15 percent for the percent error for the test and CV data sets was considered good. These "good" values for r and percent error were based on analysis of the results of many test data sets, and reflect a general

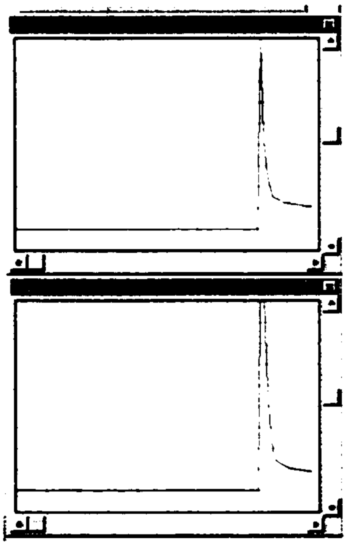


Figure 3.3 NeuroSolutions graph of training (active) and CV cost response.

level of desired response from the network, not hard and fast rules for acceptance or rejection of a trained network.

The actual predicted values for the final training run, and the test and CV runs, from the network were saved to ASCII files. The output data from the network consisted of only the desired value and predicted value. When the network is presented with an input exemplar it produces an output for that exemplar. It was possible to take the x/y coordinates of each input exemplar, pair the coordinates with the predicted output, and save those data to an ASCII file. This file was then read by an external program which created an image in memory (much like what was done for the output file in the queuing program), the predicted value placed in correct x/y location for that fire and written out to LAN file. The LAN file was converted to an ARC/Info grid, and shifted to the coordinate system of the other coverages for display.

Initial Training Trials On Individual Fires

As described in Chapter 2, the ASCII data files created by the queuing program were initially combined into three sets. A data set contained either 20, 28, or 52 percent of the data present within the fire boundary and evaluation area. Separate files were maintained for each fire, and several different combination sets were constructed to address various questions presented at the end of Chapter 1. The first network development trials were conducted on the Airport fire. This fire was chosen because it was the first fire listed alphabetically. Initial trials were conducted using the 52 percent data set for training, 20 percent for cross validation, and 28 percent for testing the trained network. Networks with 10, 25, 50, 75, 100, 150, 200, 250, ..., and 700 hidden nodes were developed. The 450-node network was the best trained network that learned to predict the test and CV data accurately. After this encouraging first trial the training and testing data sets were switched. Networks with the same series of increasing number of hidden nodes were trained using the 28 percent data set and tested with the 52 percent set.

Results for the Airport fire are presented in Figure 3.4. For this and all remaining maps of fire model results, the best way to look at the information is that grey or red inside the known fire boundary, and green or yellow on the outside of the fire boundary represent good results. The converse, green/yellow inside or grey/red outside, represent poor results. The figure shows the 52 percent and 20 percent data burn (1) or no burn (0) predictions from the trained neural network (lower map). The predicted results from the final training run (28 percent data) are shown in the top map of Figure 3.3. While technically the 20 percent data are not independent because they were used for checking the training of the ANN model, they are presented in this graphic because they were never use to modify directly any the weights of the network. The 20 percent data were only used to prevent overtraining of the network and are, in essence, a second test set. The results presented in Figure 3.4 were very good and encouraging at the time of the initial trial. There are only minor areas of false burn pixels (1/0's) slightly outside the known fire boundary or false no burn pixels (0/1's) inside the fire boundary, with less than a dozen false no burn pixels scattered inside (i.e., not adjacent to) the fire boundary. Similar networks were developed for the 10 remaining individual fires, producing results (not shown) very similar to those shown in Figure 3.4 for the Airport fire.

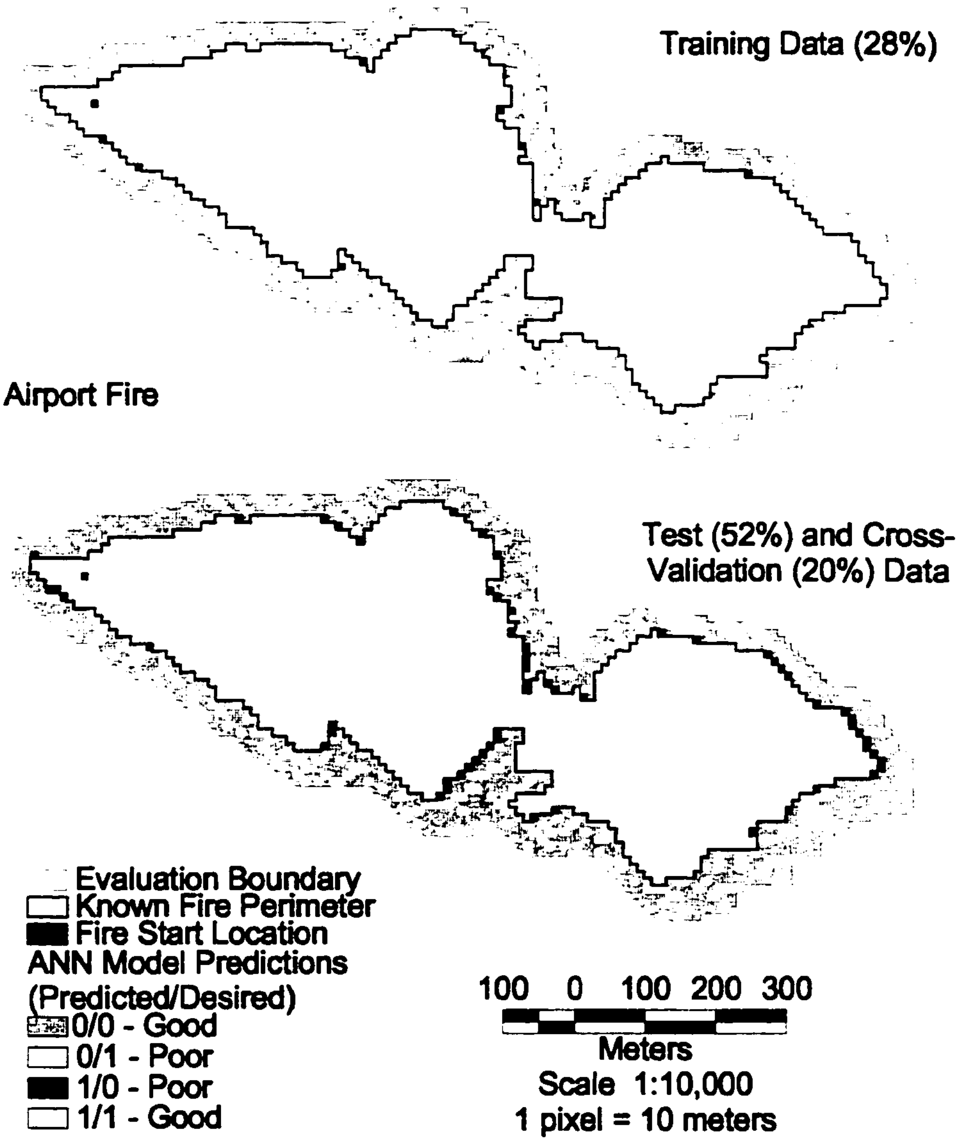


Figure 3.4 Map of burn probability estimates for the test and CV data as predicted by a ANN model. Results were obtained using 28% of the data to train the network (top map), 20% to cross-validate and 52% to test the ANN (bottom map). The training pixels are shown in white within the evaluation boundary for the fire in the bottom map.

Most of the interior false no burn pixels lead directly from and are associated with the fire start location. This is an artifact of the method used to queue the fire data, but are easily recognizable as artifacts and are unlikely to confuse interpretation. Those pixels that are the leading edge of the fire (e.g., those directly downwind from the starting pixel) appear to present the most difficult configuration for the network to understand (only one adjacent burned pixel). As a result of the queuing process, a similar artifact appears in almost every fire map presented in this chapter. This issue will be addressed more fully in the final chapter.

Nodes Analysis

The number of hidden nodes used for the results shown in Figure 3.4 is greater than the number used in later model development. As described at the beginning of this chapter, the NeuroSolutions program interface is richly complex, and the structure of these early network models is at least partially due to the initial human learning curve for using the program. Trials involving these first data sets and networks also let to a better appreciation for the size, shape and complexity of the fire environment as presented by the chosen input variables. As discussed in Chapter 1, each hidden node within a network maps a small part of the input-output data relationship. Since each node learns only a segment of the relationship, a sufficient number of nodes are needed to capture shifts in the response surface that relate to the normal variation of the data present within the fire and evaluation boundaries. Too few nodes and a network is unable to learn the full range of variation. Too many nodes and each node specializes on a very small and specific section of the data, the network over-learns (memorizes) the response surface and is unable to generalize outside of the range of known training data. These early trials looking at a large range of hidden node numbers were necessary to gauge the scope and complexity of the problem and inform later model development work.

Secondary Trials Using All 11 Fires

When using all the input data described in chapter 2 for the 11 fires (e.g., Figures 2.3), the average number of required hidden nodes was approximately 450, but ranged from 300 to 650. Given the input data, this size of multilayer perceptron will always find a solution close to a global minima in mapping the input-output relationship. When working with any new combination of the input data, a nodes analysis was conducted and outputs were visually analyzed for prediction accuracy. Changing the data subsets, namely the number of exemplars, and with that the range of variation of the input variables, would always change the number of hidden nodes necessary to accurately train and predict ANN models within the redefined fire environment.

After these initial trials on individual fires, the 28 percent data from all 11 fires were combined into a single input data file, as were the 20 and 52 percent data. The 28 percent data were then used to train a single network to predict burn probabilities for the remaining 72 percent of the data. The results for all 11 fires are presented in Table 3.1 and Figures 3.5a, 3.5b and 3.5c. With a larger range of variation within the input data, the ANN model predictions are understandably more variable than the individual fires as exemplified by

Figure 3.4. This is evident in the greater number of red and yellow pixels along the fire perimeter and radiating out from the fire start location.

Table 3.1 Summary of desired versus predicted values for all 11 fires on the Huron National Forest. Results are separated for "no burn" (desired = 0) and "burn" (desired = 1) pixels. The first value is total number of pixels and the second is the percentage for the group.

	Desired/Predicted		Desired/Predicted	
Fire Name	0/0	0/1	1/1	1/0
Airport	935 (90%)	102 (10%)	1927 (95%)	91 (5%)
Anniversary	398 (89%)	51 (11%)	717 (93%)	51 (7%)
ATV	2885 (86%)	472 (14%)	24469 (99%)	171 (1%)
Busch	321 (89%)	39 (11%)	327 (90%)	37 (10%)
Cooperation	509 (92%)	44 (8%)	842 (92%)	76 (8%)
Fuelbreak	1217 (94%)	76 (6%)	1760 (95%)	102 (5%)
Happy Hardwood	406 (87%)	62 (13%)	1105 (96%)	47 (4%)
Mile and a Half	815 (95%)	42 (5%)	561 (92%)	49 (8%)
Powerline	613 (89%)	74 (11%)	815 (94%)	48 (6%)
Tuttle Marsh	1550 (90%)	165 (10%)	3633 (96%)	165 (4%)
Unhappy Camper	1393 (87%)	212 (13%)	6871 (98%)	153 (2%)

Trials Using Data Subset By LTA

The overall results from the total combined data sets were very promising, and the next trials therefore involved some subset of these 11 fires. Two basic ways of dividing the 11 fires were assessed. One method was to segregate the fires by month of occurrence or year of occurrence, and the other was to sort by ecoregion. Subsetting by ecoregion was chosen as the most informative method for addressing the questions presented in the Proem.

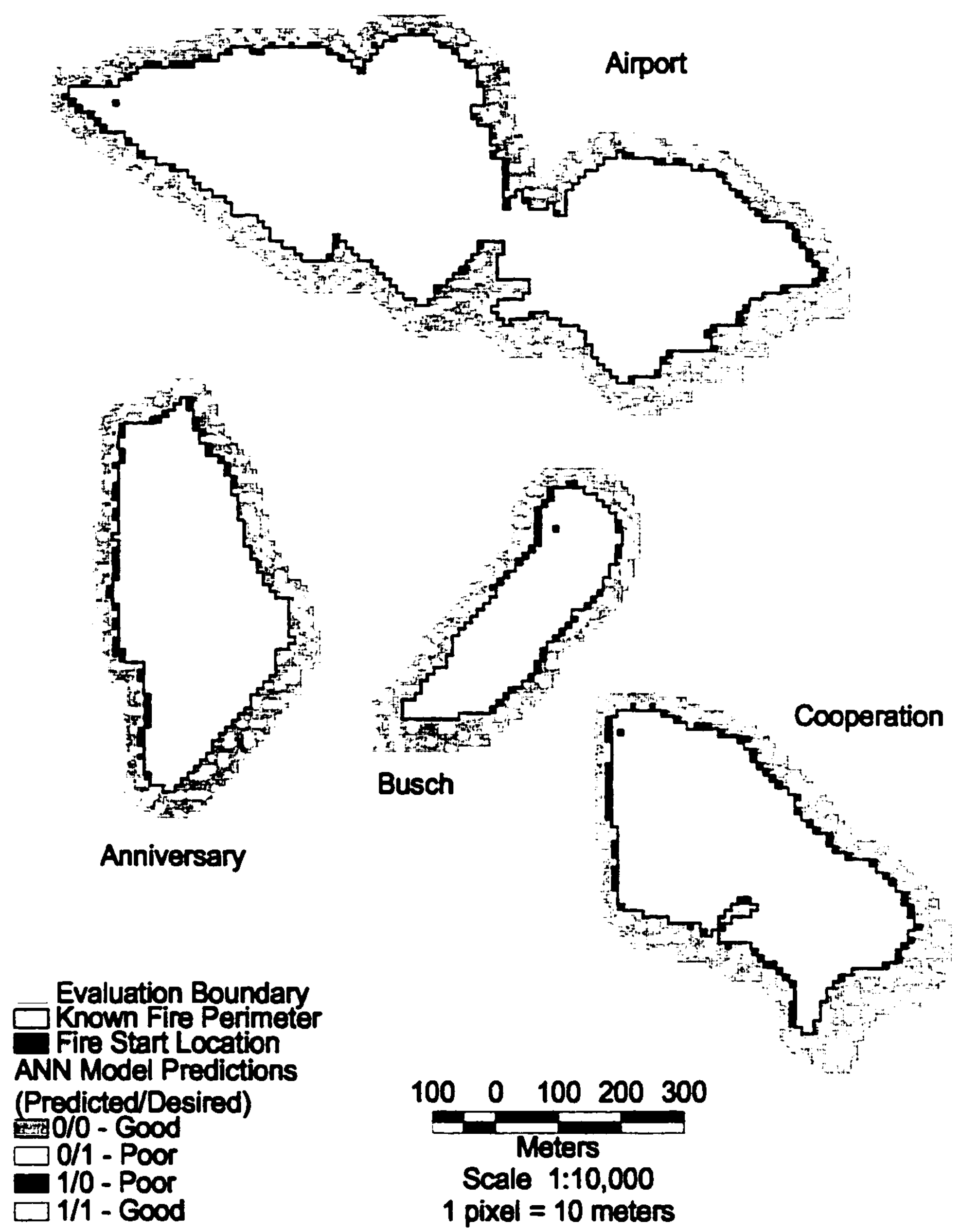


Figure 3.5a Comparison of predicted versus desired output from 300 node ANN model trained with 28% of the data for all 11 fires. Training pixels are shown as white within the evaluation boundary for each fire. Figures 3.5b and 3.5c show similar information for the remaining seven fires. Refer to Table 3.1 for Confusion Matrix totals.

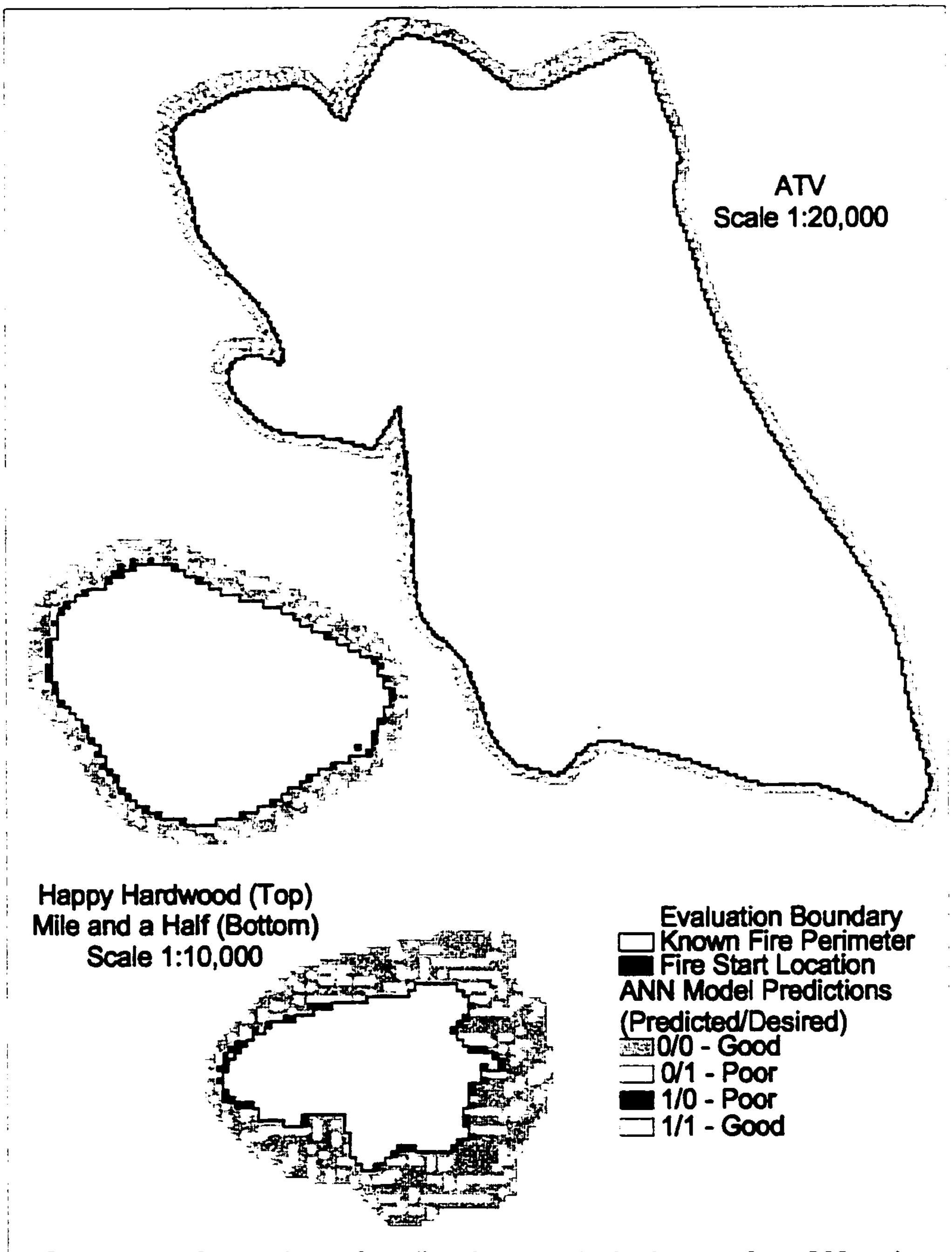


Figure 3.5b: Comparison of predicted versus desired output from 300 node ANN model trained with 28% of the data for all 11 fires. Training pixels are shown as white within the evaluation boundary for each fire. Refer to Table 3.1 for Confusion Matrix totals. 1 pixel = 10 meters for all fires.

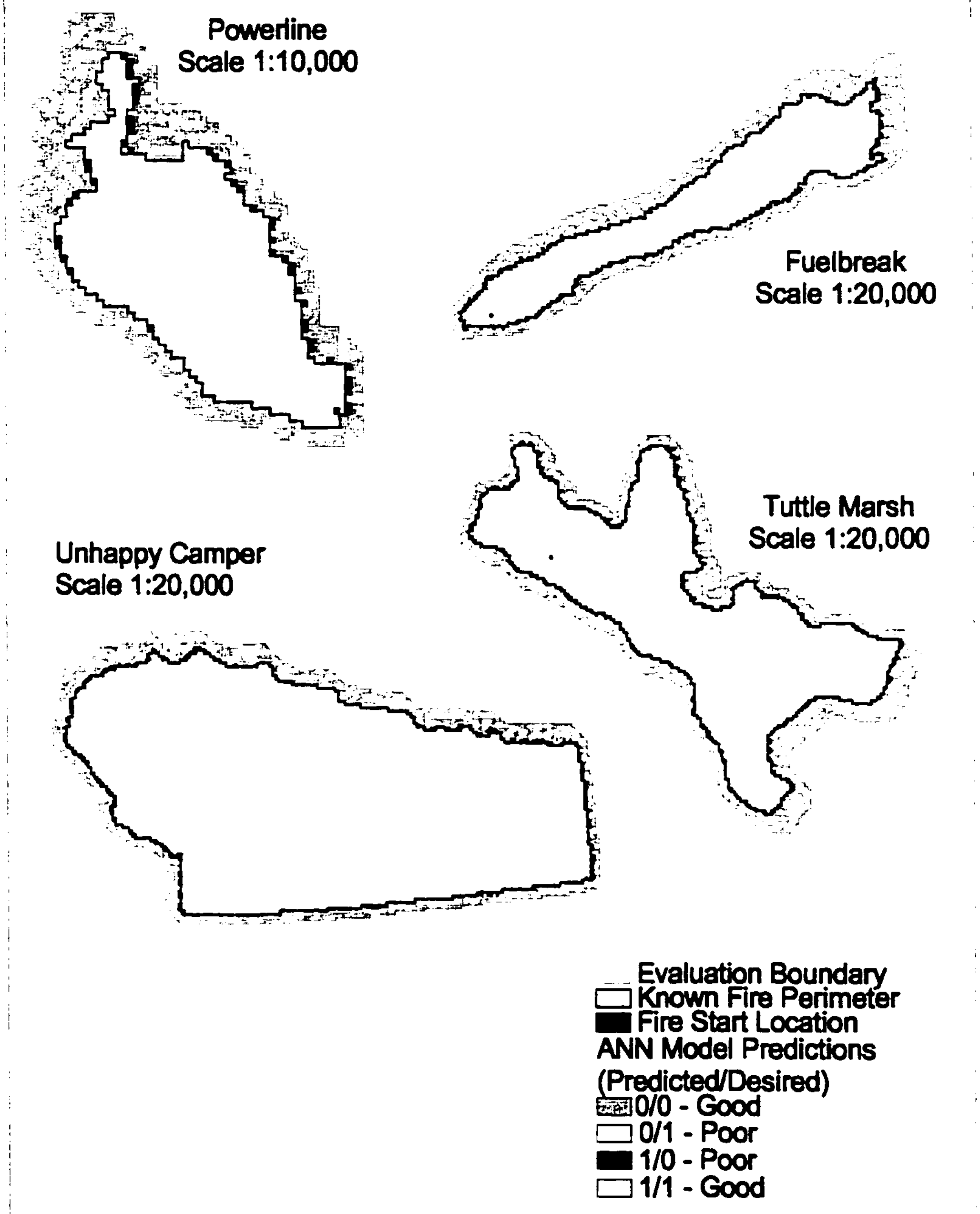


Figure 3.5c: Comparison of predicted versus desired output from 300 node ANN model trained with 28% of the data for all 11 fires. Training pixels are shown as white within the evaluation boundary for each fire. Refer to Table 3.1 for Confusion Matrix totals. 1 pixel = 10 meters for all fires.

The five fires present on Ecoregion 212Hr, LTA 1, include Anniversary, Busch, Cooperation, Fuelbreak, and Mile and a Half (Mile). The fires were initially divided into training and testing groups of roughly equal size. The first set (ABC) contained all pixel data from the Anniversary, Busch, and Cooperation fires (4719 pixels, 68 acres). Data from the Fuelbreak and Mile fires (6304 pixels, 82 acres) comprised the second set (FM).

Networks of various sizes were constructed and trained using 80 percent of the ABC data, with 20 percent used as CV data. Total error values peaked early and dropped rapidly before beginning to level out for these trials, as is typical and expected during ANN model development. Usually, after the training error value levels out, the CV incremental error drops to near zero and the stopping criterion is met. For these networks, regardless of hidden neuron number, the training error oscillated about a straight line for hours before meeting the stopping criterion (e.g., as shown in the active cost graph in Figure 3.2).

Changing the Stopping Criterion and Weight Update Method

A switch was made from batch mode learning, where errors are averaged over all training exemplars before the network weights are updated, to on-line learning where the error from each exemplar is used to update the weights. While computationally slower, on-line learning is generally a better weight update method to use with large training data sets (Neil Euliano, pers. comm.). This worked to stabilize the error, but using CV data to stop the training still did not seem to produce a good network. Trials that were stopped early seemed to do better than those that stopped when the CV stopping criterion was reached: overtraining was occurring.

Instead of using CV data to stop training, the stopping criterion was changed to a 0.0005 absolute incremental change in the training error. Several trials using the same instantiation of a neural network (i.e., the same set of randomized initial weights) were conducted using 0.0001, 0.0003, 0.0005 and 0.0008 values for the stopping criterion. The 0.0005 value appeared to present the best value for stopping, given the input data and hidden node configuration used. Using the very low stopping rate (0.0005 percent) appeared to capture the bottom of the error curve, approaching the global minimum in the error surface while providing an independent method to stop training before overtraining occurred. The use all the pixel data from the training fires was now possible since no CV data were needed.

Resuming LTA Subset Trials

Two networks were developed, one using the ABC data set for training with the FM data set used for testing, and one using FM to train and ABC to test. Results are presented in Figures 3.6a and 3.6b. The networks were able to learn and predict quite well for the training data as shown in the top three fire maps in Figure 3.6a and the bottom two fire maps in Figure 3.6b. What both networks failed to do was predict with any accuracy for the test fires, as shown by the bottom two maps in Figure 3.6a and the top three maps in Figure 3.6b. From looking at the fire environment variable values, it was hypothesized that wind direction may be having an undue influence on prediction accuracy. The ABC fire complex had wind directions

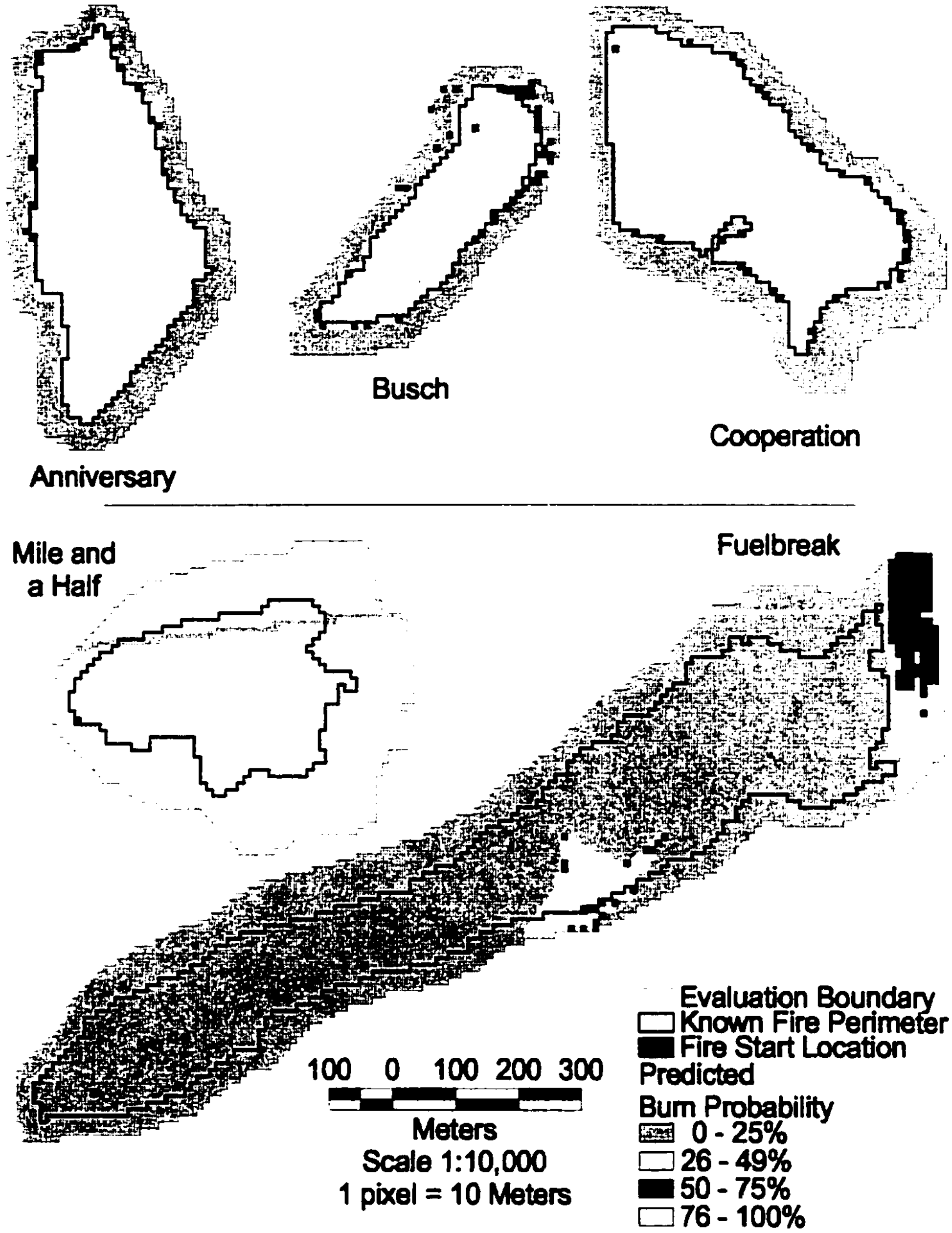


Figure 3.6a Training and testing results for 212Hr1 fires. Best results from a nodes analysis using the top three fires (Anniversary, Busch and Cooperation) for training and the bottom two fires (Mile and a Half and Fuelbreak) for testing. Final ANN model had 450 hidden nodes.

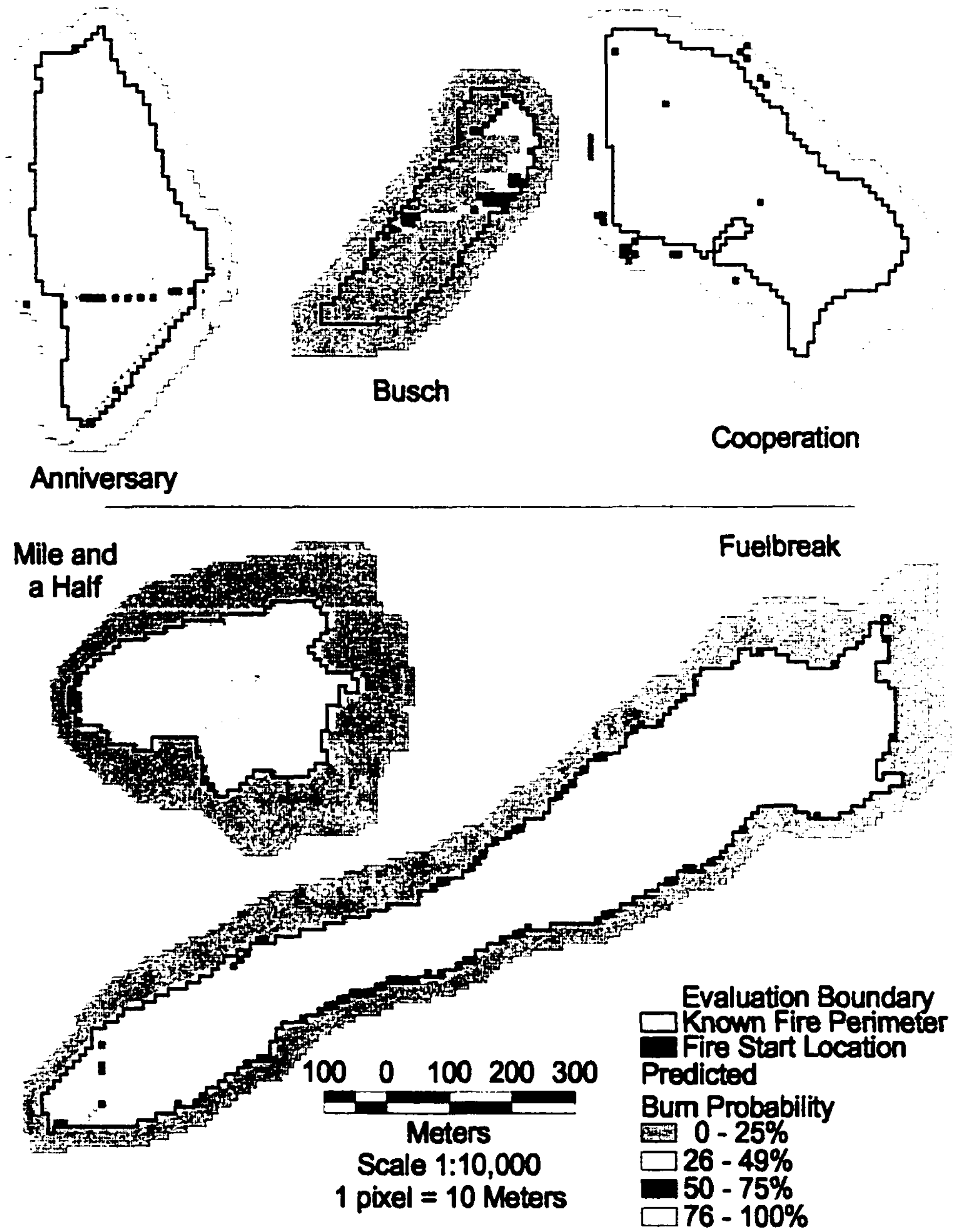


Figure 3.6b Training and testing results for 212Hr1 fires. Best results from a nodes analysis using the bottom two fires (Mile and a Half and Fuelbreak) for training and the top three fires (Anniversary, Busch and Cooperation) for testing. Final ANN model had 450 hidden nodes.

ranging from southwest to southeast whereas the FM data consisted of east and northeast winds. Again, considering total area and number of exemplars, reconfiguring the subset of fires from ABC-FM to BF-ACM would work if BF was used for training and ACM was used for testing but probably not the converse. Instead, a new subset was made of the ABCF fire data with only the Mile fire used for testing the network. This increased the number of training exemplars (from 4719 to 9022) and the wind direction for the Mile fire fell within the range of values for the ABCF fires.

For the results shown in Figures 3.4 through 3.6, network node type (Tanh) and learning method (momentum) did not seem to be a factor. One possible reason for this is because the first ANN models were trained using data from only one fire or all 11 fires. In both cases, there was most probably a large global minimum present in the error surface that almost any network configuration would have found given sufficient hidden nodes. Working with a smaller subset entailed fewer exemplars, with a narrower range of variation in the input data presented to the network during training. Also, with both a more specific response surface and a smaller global error minimum, the possibility of having one or several large local minima increased. These first trials were easy test cases for a neural network since the training and testing data were equally distributed across the spatial extent, therefore capturing fully the known range of variation.

The network used for the results shown for the Airport fire in Figure 3.4 was very large (high number of hidden nodes) with respect to the number of input exemplars. The network that resulted was able to accurately predict the test pixels was because the search space was very small. Also, it is likely there were a number of nodes that contributed little or nothing to predicting the output value (i.e., there were redundant nodes). With the subset data of four training fires (ABCF) and one test fire (M) all of the hidden nodes were needed to produce a correct output response. The number of weights with respect to number of input exemplars became more of a factor. In essence, this is a middle number problem, namely using a large number of variables as inputs and having a limited range over which that combination of variable values is valid for use in prediction.

Additional Alterations to Network Topology To Improve Prediction

Learning to predict using training data from only one fire (e.g., the totals in the 28 percent column, Table 2.2) was a straightforward task for a neural network, and learning to predict using the massive amount of training data (21207 pixels) from 11 fires was not really more difficult, it just took longer. Learning from a small set of fires, and predicting in an area where the network had not seen any portion of those data, was more of a challenge in network development. Since the data sets were essentially fixed (the subsets based on LTA were of most interest from a research standpoint), changing the topology of the network was the next logical place to look for improvement in response from the ANN models.

The nonlinear aspect of all the network nodes was changed from Tanh to sigmoid. As discussed at the end of Chapter 2, the difference between the two node types is that the nonlinearity function of Tanh neurons produces output from -1 to +1, where sigmoid neurons produce output from 0 to 1. Since the desired network prediction is either 0 (no burn) or 1 (burn) sigmoid neurons were a more logical choice. With sigmoid neurons the input values are normalized to between 0 and 1, as are the initial, randomized weight values, instead of -1 and +1.

The third change in network topology was changing the learning rule. Learning was switched from momentum learning to delta-bar-delta (D-B-D) (Principe *et al.*, 2000). As discussed in Chapter 2, using D-B-D makes learning a bit more unstable since the weights tend to jump around more than with momentum learning. A network configuration using the combination of different learning rule, sigmoid neurons and on-line learning seemed to work well for the subset data.

Resuming LTA Subset Trials, Again

Using all the ABCF input data, numerous ANN models using the new topology and various hidden node numbers were trained and tested on the Mile fire (Figure 3.7a, 3.7b and 3.7c). Based on previous analyses and the theory that the ABC-FM data pairings did not work well because of wind direction the results shown in these three figures were expected. While there were some networks that predict quite well, as evident in the 150-node results in Figure 3.7a for example, the overall results indicate that the networks are very sensitive to the initial random weight values and there are insufficient input exemplars to adequately adjust the weights.

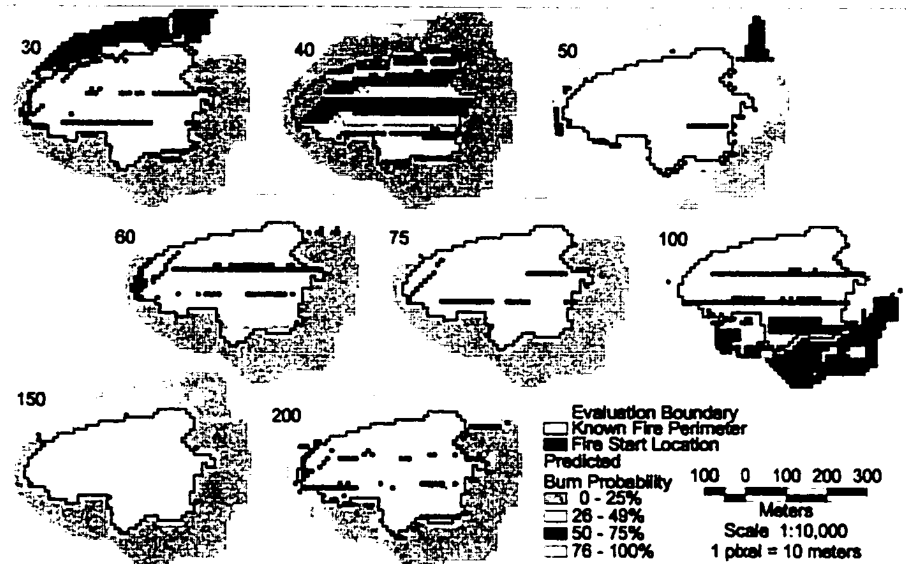


Figure 3.7a Test results for the Mile and a Half fire using the Anniversary, Busch, Cooperation and Fuelbreak fires for training the ANN. The numbers at the upper left of each fire map indicate the number of hidden nodes in the predictor network. Two additional trials of each node number were conducted, with Figures 3.7b and 3.7c showing those results.

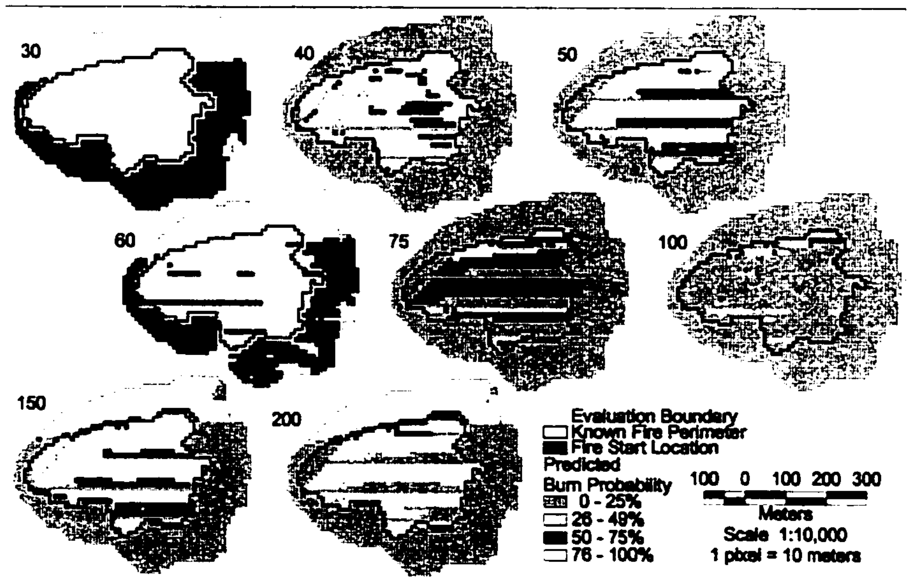


Figure 3.7b Test results for the Mile and a Half fire using the Anniversary, Busch, Cooperation and Fuelbreak fires for training the ANN. The numbers at the upper left of each fire map indicate the number of hidden nodes in the predictor network.

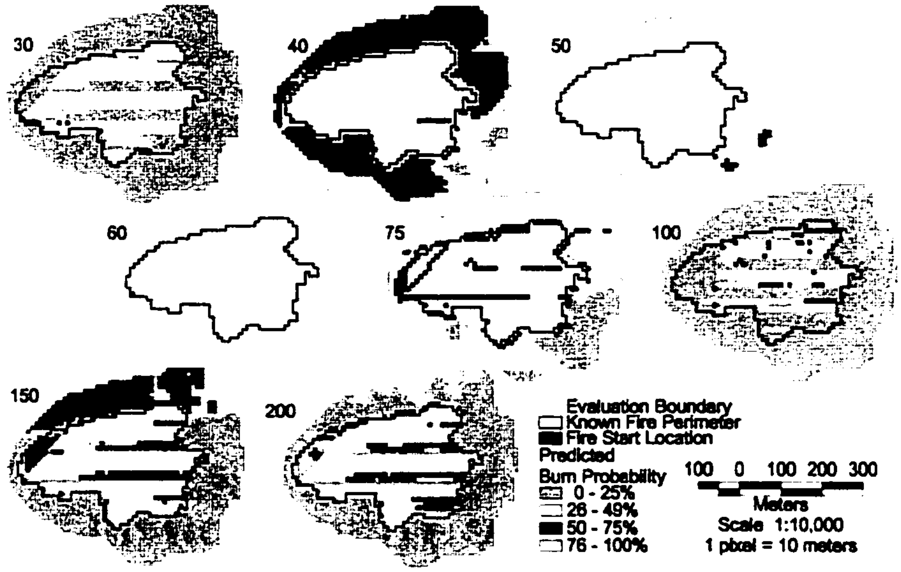


Figure 3.7c Test results for the Mile and a Half fire using the Anniversary, Busch, Cooperation and Fuelbreak fires for training the ANN. The numbers at the upper left of each fire map indicate the number of hidden nodes in the predictor network.

Furthermore, prediction in the upper quarter of many of the graphics changes significantly (e.g., Figure 3.7a, 60 and 70-node), but only outside the known fire boundary. From looking at the original data coverages, it was apparent the area north of the northern fire boundary reflected a change in available input data. Stand type, stocking density and year of origin data were not available for the southern 3/4's of the Mile evaluation area since it occurred mostly off of HNF property. So, while the prediction within the fire boundary remained good in many cases (30, 50, 60, 75, 150, and 200-nodes), once outside the known burned area the network was uncertain as to whether to start a fire or not. The network was again getting the full range of input data (i.e., it was getting too much information). An alternative explanation is that the predictions within the fire boundary are actually poor, since the network was getting values of -1 (no data) for 27 of the inputs instead of stand age, density and year of origin data.

The apparent sensitivity and instability of the networks, presumably a result of initial weight values and missing test data, prompted a thorough reconsideration of both the data and network structures. If wind was the only problem with the ABC-FM trials, then the results of the ABCF-M trials should have been much clearer than those shown. It is probable that with a small number of hidden nodes (e.g., 30, 40, 50) there were sufficient training exemplars, with respect to number of weights present in the network, but insufficient nodes to generalize about the response surface. For an intermediate number of nodes (e.g., 60 or 70) there were probably sufficient nodes to learn most of the response surface, but not all. The 150 and 200 node graphs shown probably represents the right size of network but this was pushing the limit of the network training routines, given the number of input exemplars. Networks with greater than 200 hidden nodes were trained, all with very poor prediction results.

Altering Inputs To Improve Prediction

With no other changes in network topology possible, what were assessed to be minor environmental input variables were removed. The pruning of the inputs was done to reduce the required number of network weights. Every input parameter removed reduced the number of weights by a factor of nine times the number of hidden nodes. Since the ABCFM fires were all on the same LTA, that input variable was deleted. Ownership was deemed a minor variable and deleted as well. Beyond these variables there was no clear way of selecting the next variables to remove. For example, while the pixel values for most regions of the roads and rivers coverages were 0, they were important, non-zero features in select regions (e.g., the Tuttle Marsh and Powerline fires). Trained networks were providing no better prediction with the LTA and ownership variables removed, so a second reassessment of the problem suggested deleting all except the very basic input variables.

Essential inputs were determined to be wind speed and direction, elevation, absolute x/y coordinate, and the spectral reflectance values contained in the DOQ and TM layers. This reduced the input vector from 197 to 134 in number, and required a much smaller hidden node layer. A nodes analysis was again conducted with nodes ranging from 5 to 50. Approximately 100 trials were conducted, of which one particular model with 12 hidden nodes did a very good job of learning the ABCF training data as well as predicting the Mile, Airport, and Tuttle Marsh test data (Figure 3.8a). The Airport and Tuttle Marsh fires occur on the same subsection (212Hr) as the ABCFM fires but on different LTAs (5 and 7, respectively). Given these encouraging results the same model was used to predict burn probabilities for the four remaining fires (Figure 3.8b).

As shown in Figure 3.8b, results for the ATV fire are clearly a failure of this particular model. This is not surprising since the ATV fire occurs at an elevation range well above any of the training data, is an order of magnitude larger in size than the training fires, and is geographically on a very different portion (Ecoregion 212Hq, LTA 1 and 2) of the Huron National Forest (Figure 2.1). The three other fires shown in Figure 3.8b are also elevationally higher and ecoregionally distinct from the training fires, though they are roughly similar in size. While the model predicted well within the known fire boundary for these three fires, it predicts too high a burn probability for pixels bordering the fire perimeter to be acceptable as an operational model. This is most likely a result of the ANN operating outside of the known range of variation for the input variables from the training fires. The elevation and spectral information for the fire shown in Figure 3.8b are most likely responsible for the increased burned probability predictions.

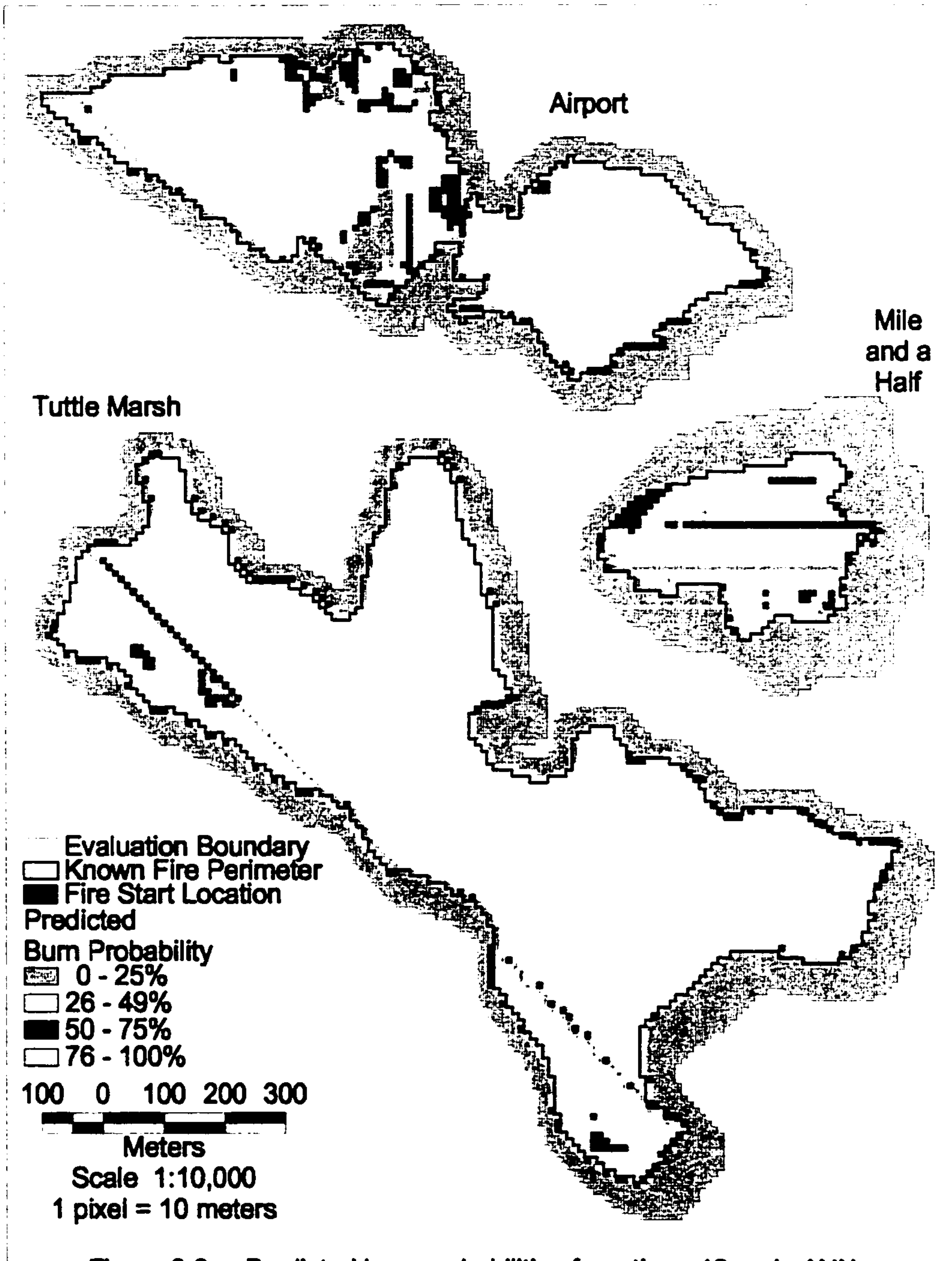


Figure 3.8a: Predicted burn probabilities from the a 12 node ANN trained using only wind speed, wind direction, DOQ, TM, DEM and absolute x/y coordinates. Training fires: Anniversary, Busch, Cooperation and Fuelbreak.

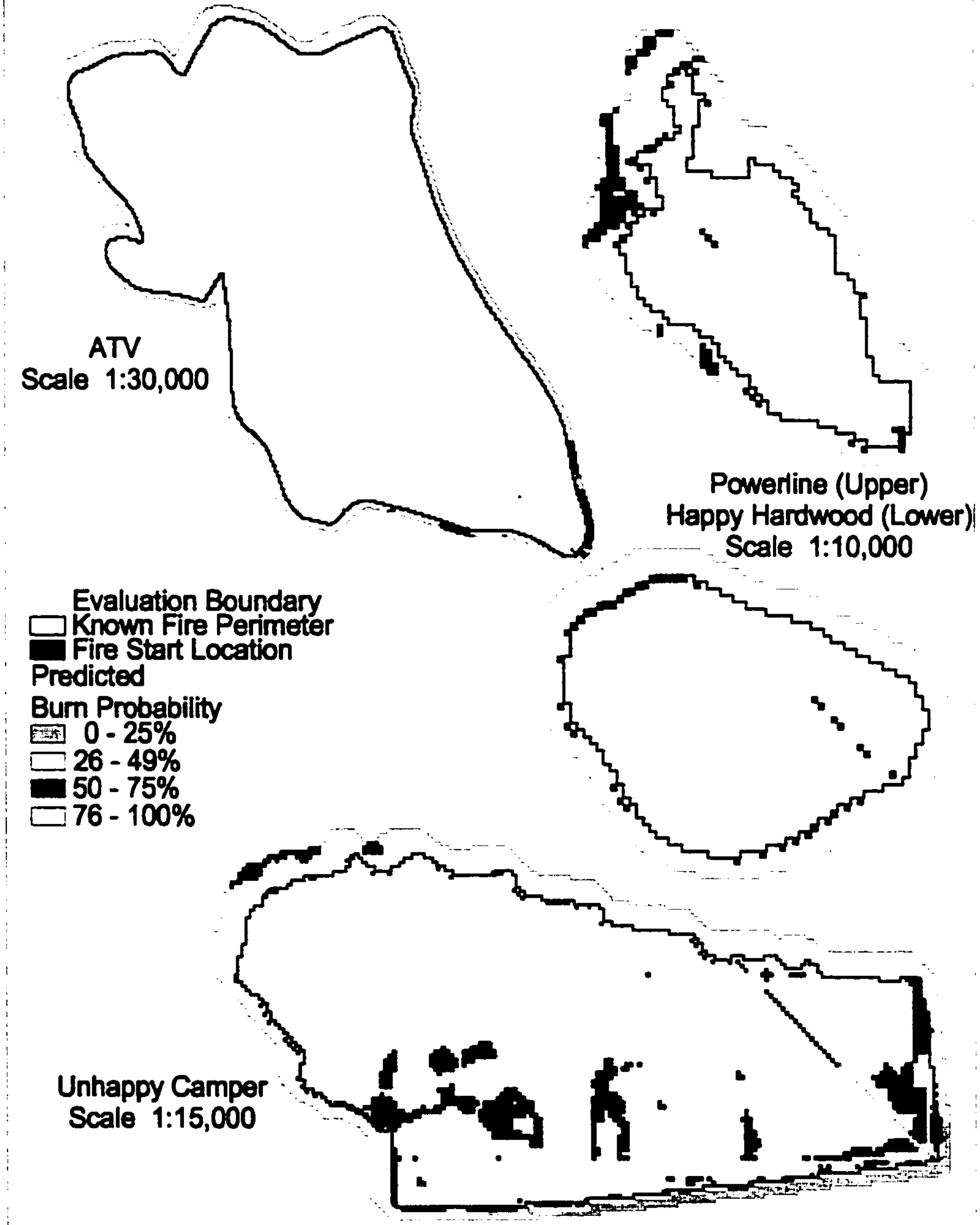


Figure 3.8b: Predicted burn probabilities from the a 12 node ANN trained using only wind speed, wind direction, DOQ, TM, DEM and absolute x/y coordinates. Training fires: Anniversary, Busch, Cooperation and Fuelbreak. 1 pixel = 10 meters for all fires.

4

Concluding Discussion

These ANN models seem to capture quite well the meso-scale fire environment as represented by the chosen input variables. The models developed to-date are supportive of the meso-scale fire modeling theory outlined in Chapter 1. However, at this point these models are not yet fully operational, and comparative analyses to prove or disprove hypotheses seem premature. Inputs to all of the ANN models developed to-date contain information on the known fire burn area and boundary (i.e., *a priori* knowledge of where the fire spread to). Each input pixel knew the fire burn status of neighbor pixels, as described in Chapter 2 (Figure 2.5). Using the known arrangement of the fire front to make a burn/no burn decision for a given pixel is a very reasonable approach for modeling fire at any scale. To really prove the efficacy of these ANN models, neighbor burn status must come from predictions from the ANN model, not from known fire boundaries.

At this point in the exploration of meso-scale fire theory, there is a bit of a circularity in the model logic with respect to the neighbor burn status. If I told the model that "burn" is the desired answer when three or four of the adjacent pixels were burning, it is quite logical that the ANN produced a burn prediction. If none of the neighboring pixels was burnt, then a no burn prediction was likely. In light of this, the results shown in Chapter 3 seem somewhat obvious, and at one level of analysis they are. Alternatively, an analysis of the poorly predictive models (e.g., Figure 3.6a (bottom), Figure 3.6b (top), Figures 3.7a-c, and Figure 3.8b) shows an interesting trend. In Figure 3.6a, for example, the results from the final training run, shown in the top three maps, indicate a high training accuracy. The bottom two maps, the test data from that trained network, show very poor predictive accuracy.

What is notable is the degree to which the predictions are poor: the network either burns almost everything (Mile) or almost nothing (Fuelbreak). Figure 3.6b, using Fuelbreak and Mile to train, produces a similar all-or-nothing response for the three test fires. Many of the maps in Figures 3.7a-c show total burn or no burn, but a few start to have mostly burn inside the known fire boundary, and mostly no burn outside (e.g., the 150-node map in Figure 3.7a). The networks started to learn where different combinations of wind and neighbor burn status mattered, but was still confused by the extra input variables.

What is striking about the predictions shown in Figure 3.8a is that both error types, always predicting burn where there was none or none where there was, disappeared simultaneously. The network had learned that something significant changed at the boundary. Specifically, the network learned that the burn status arrangement of neighboring pixels and wind direction was important in predicting whether the pixel being evaluated would burn. For this research to progress in the future, I needed to know that an ANN model was capable of learning this relationship.

Figure 4.1 shows the results from Figure 3.8a as predicted/desired pairings for more easily locating errors. For Figure 4.1, predicted values from 0 to 49 percent were reclassed to a value of 0 (no burn), and values from 50 to 100 percent were reclassed as 1 (burn). The issue of the queuing artifacts (straight lines) stemming from the start pixel location can be dealt with using alternative models, as discussed below. The large, solid block errors inside both the Airport and Mile fire boundaries result from burn status and wind interacting with the other input variables. It is likely that additional training data could help to limit those types of errors. The yellow pixels just inside and the red pixels just outside the known fire boundary present the greatest challenge to the network in term of prediction. They also present the greatest challenge in future model development. When the neighbor burn status values are based on predicted output, both the yellow and red errors will tend to propagate. Some approaches and solutions are discussed below. Others I have not yet envisioned, nor could I until I reached this point in my research. Having a network that can readily deal with the obvious burn regions and obvious no burn regions, I can now elaborate the model environment to better assess fire boundary predictions. As stated in the Proem, this dissertation outlines a career's worth of future research avenues.

Proem Revisited

The three questions presented at the end of the Proem, while not constructed as hypotheses to be accepted or rejected, can be addressed in light of the results presented in Chapter 3. In essence, the first two questions (A1 and A2) are: can artificial neural networks learn to predict wildfire spread patterns and does it matter to the ANN which ecoregion the fire data

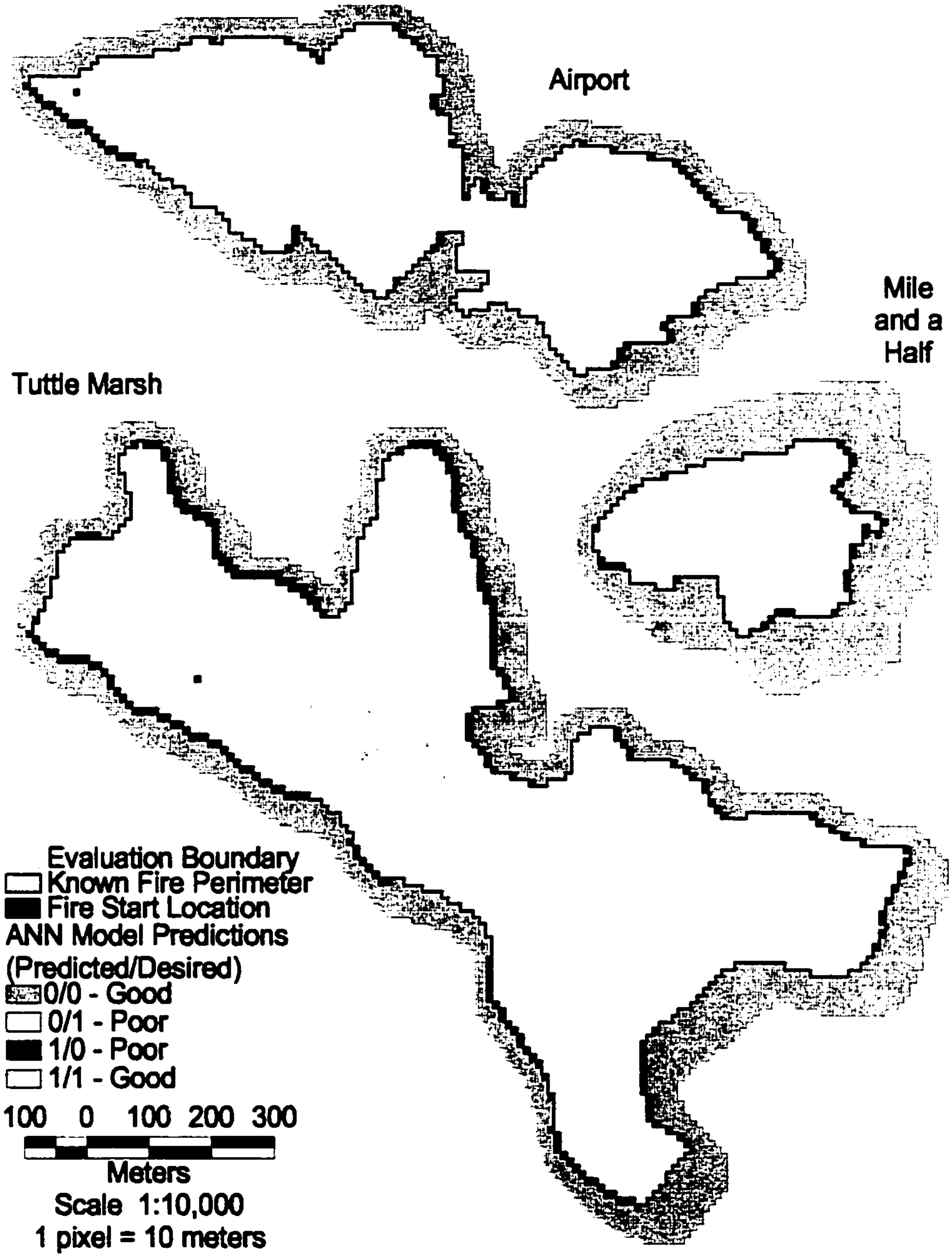


Figure 4.1 Results from Figure 3.8a presented as predicted/desired output values to show error locations.

come from? As presented in Chapter 3, 11 ANN models of wildfire spread were successfully developed for 11 Huron National Forest wildfires using 28 percent of the pixel data for training and 72 percent for testing each individual fire. Also, a single network was developed using 28 percent of the data from all 11 fires to accurately predict burn probability for the remaining 72 percent of the evaluation area pixels for all 11 fires.

Attempts to train and test networks using a subset of fires were not successful, regardless of network configuration, when all available input variables were used. Through a combination of altering network topology and reducing the input variables to a minimum representation of fuel, climate and topography, a trained network (using the Anniversary, Busch, Cooperation and Fuelbreak fires) was achieved that predicted within LTA (the Mile fire) and across LTA (the Airport and Tuttle Marsh fires) in one Subsection (212Hr) with good success, but with limited success across Subsection (212Hm and 212Hq). So, yes, ANNs can learn the complex fire environment well enough to predict wildfire spread pattern, and, yes, ecoregion appears to matter in the prediction accuracy. However, because model failure across ecoregion boundaries is confounded by and may be and artifact of input data range and variation, these results are not clearly defined by these trials.

The third question (B1), concerned with understanding controlling factors, is much more difficult to address in light of the results presented. On the surface I can answer yes, ANNs can sort out what levels of analysis within the complex fire environment to use in predicting fire spread. How they are able to do this, and under what circumstances, remains an open area of future study. The following discussion of model operation, sensitivity and scaling issues addresses more fully why an answer to B1 is not readily evident.

Achieving A Fully Operational Model

To develop a fully operational meso-scale ANN fire model several issues need to be addressed. The next testing phase in development of these meso-scale models should involve basing the neighboring pixel burn status on the actual predictions from the ANN, not from known burn location information. As is evident from the results shown in Figures 3.3, 3.4a-c and 3.7a, accurate predictive fire models are possible using ANNs, and a fully operational model should produce output of similar accuracy. The queuing process would remain the same, and training of the models could still occur in a manner similar to that described in this document, though some external changes in model operation would need to be made. Three possible changes involve thresholding, a mixture of models, or neighborhood smoothing.

Thresholding

The ANN predicts a decimal burn probability estimate ranging from 0 to 1, but the networks were trained using integer values of 0 or 1. A reasonable approach for using these ANN-predicted output values would consist of thresholding the output prior to their use in the model (e.g., a prediction from 0 to 49 percent would be set to 0, from 50 to 100 percent to 1).

The actual (decimal) predictions could still be saved for analysis, while the model would receive input values in keeping with those it was trained on.

Mixture of Experts Models

A "mixture of experts" modeling approach (Principe *et al.*, 2000) could include both fuzzy logic and decision rules to select which of many networks would be used for burn predictions based on input variable values and burn configuration. One model mixing approach could include averaging the output from two or more networks. For example Figure 4.2 shows the mean predicted value for the variously-sized networks shown in Figures 3.4a-c. As shown in Figure 4.2, the 40, 75 and 150-node networks have a thresholded, mean predicted value much improved from the results for any single instantiation of those networks as presented in Chapter 3. Also, the issue of the queuing artifacts associated with the start location pixel could be addressed by having a separate model that predicts burn probabilities only for pixels of that type. Furthermore, decision rules that select between models would solve the problem of loss of predictive accuracy when crossing ecoregional boundaries (e.g., the fire results shown in Figure 3.7b).

Smoothing

Neighborhood smoothing (e.g., majority filtering) could be used after an initial presentation of the queued pixels to a network. A several-pixel wide buffer should be maintained along the predicted/known fire boundary. As shown in Figure 4.2, use of a smoothing filter on the

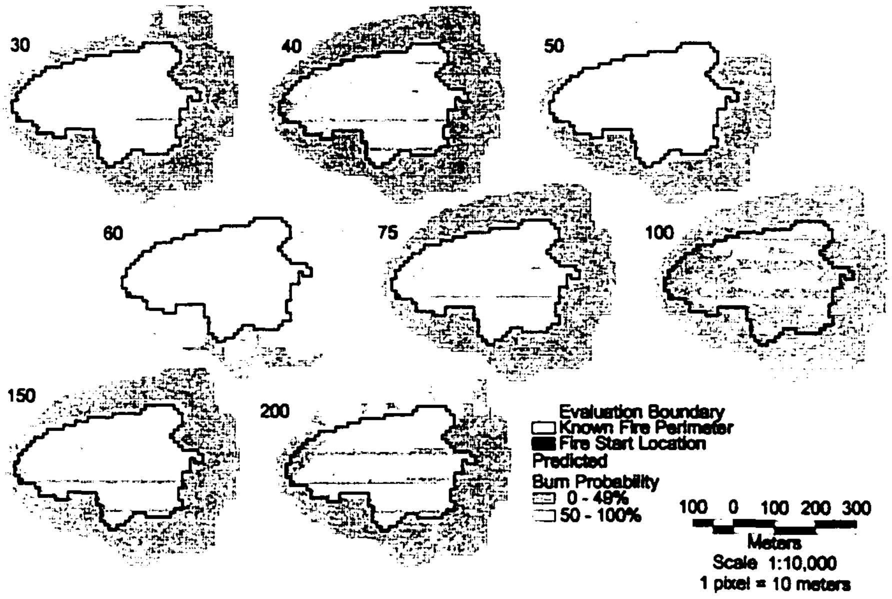


Figure 4.2 Mean predicted value from Figures 3.7a-c.

40, 75, and 150-node results would remove the queuing artifacts. Assessing the predicted accuracy from presenting the network with the same fire while using the smoothed fire map as input data may be an interesting experiment.

Sensitivity

General Concepts

Within the ecological literature on ANN model development, discussion of model sensitivity varies from none at all to very explicit. Some briefly address the issue (e.g., Manel et al., 1999; Dagorn et al., 2000; Chon et al., 2000), mostly in terms of using "sensitivity" during the development phase to reduce the number of network inputs prior to conducting "real" tests of the ANN in prediction (e.g., Zealand et al., 1999). Haykin (1994), in an oft-cited textbook on neural network development does not include the term sensitivity in the index or discuss it in the chapter of multilayer perceptrons (the type of ANN model used in this research). A recent, excellent, review (Maier and Dandy 2000) of 43 papers describing the use of ANN models in water resources forecasting summarized many aspects of model development and testing as described by the various researchers, but did not report if "sensitivity" analyses were conducted in the body of the review. Only in their conclusions do the review authors discuss the need for sensitivity analyses in the future and cite one paper (Maier et al., 1998) that used sensitivity analyses to extract knowledge from a trained network. In a recent, comprehensive textbook on ANN modeling, Principe et al. (2000) present one approach to conducting a sensitivity analysis on ANN models, which is further discussed below (see Approach #1).

Every change in structure of an ANN model, including hidden node number, learning rule, stopping criterion, and input node number is essentially a response, on the part of the model developer, to a perceived sensitivity of the model and modeling environment. Note the term "model developer" is used in the preceding sentence, not "model builder," because ANNs do not involve model building in the conventional sense. A change in the number of input or hidden nodes (e.g, the nodes analyses discussed in Chapter 3) creates a new ANN model, not just an altered version of the previous model. Nodes are added or subtracted based on subjective and objective assessments of the learning rate and predictive accuracy. Also, as discussed in Chapter 3, changing the type of transfer function used in the nodes (e.g., Tanh versus other sigmoid), the learning rule (e.g., D-B-D versus momentum) and the weight update mode (e.g., online versus batch) alters the model structure and the search space for minimizing the error surface.

During the first ANN training efforts, slope and aspect were included as inputs. Early ANN model training accuracy was poor. The region of Michigan being modeled is relatively flat, and this was reflected in the slope and aspect coverages derived from the DEM. Since the actual elevation data values were used as inputs, and suspecting that there was little additional signal coming from the slope and aspect data (indeed, presumably more noise than signal) I removed those two inputs. This reduced the size of the network and improved training accuracy. As development trials described in Chapter 3 continued, every removal of a categorical (discrete) variable improved model training accuracy and reduced the size of the ANN structure. Eventually all that were left as inputs were continuous variables.

For the fire environment as envisioned and in the final 12-node model developed, it appears categorical variables (especially derived, discrete classifications) create instabilities in ANNs, making them very sensitive. Working from continuous variables, collected by human-built sensors that sample the environmental continuum in as continuos a manner as is possible given the grain of the sensor or collection technique, appears to present a clear signal to and allows for stable development of neural network models. The key point of all of this is to remember that any change in model structure creates an entirely new model that is a truly separate system description at several levels. This presents a problem for comparison between reparameterized and restructured ANNs. Perhaps the reason that papers describing the development and testing of ANN models do not often directly address sensitivity analyses is that the process of configuring and training a network implicitly addresses and minimizes the most sensitive aspects of the environment being modeled, resulting in a stable, predictive network.

Specific Analyses: Two Approaches

When testing a traditional mathematical model, it is common practice to use the same starting conditions (e.g., input data, random number seed, etc.) and vary internal parameter values in a systematic manner to gauge the magnitude of effect on the generated output. This tests the sensitivity of model predictions to changes in the internal structure. In something of a role reversal, the input variables (and starting conditions) become parameters, the internal model parameters become variables, and output values are compared to a base value. The case for ANN models is almost opposite. Once training is completed, the weights (variables during training) within the model can now be thought of as parameters, and the input data (parameters during training) are the variables that can be changed to assess the effect of those changes on the output.

Given that the input data are to be varied, two basic manipulations are suggested. One approach involves much the same process as a traditional model sensitivity study, that is, altering parameter values (the input data in ANN terms) by some set amount and assessing the impact on the output. A second approach involves turning off or neutralizing an input node and assessing what effect the complete loss of signal for one input has on the predicted output. For the ANN fire model, this would involve turning off the signal from 9 nodes, one node for each of the 9 pixels represented in the input data vector. Results from both approaches are presented below, though the meaning of the comparisons is open to interpretation.

Approach #1

Conducting a sensitivity analysis (Principe et al., 2000) within the NeuroSolutions program consists of using a trained network and reassessing any training or testing data by altering the input values and measuring the resultant change in output value. More traditional modeling methods use a similar process, altering parameter values by some set percentage and reporting the effect on output (e.g., Mladenoff and He, 1999; Schindler and Eby 1997). Data values presented to the first input node are multiplied by a factor of 1.1. All exemplars are then presented to the ANN, and the difference in network output between the original and modified values for the first input node is recorded. The same procedure is followed for each input node in sequence. The input nodes are then ranked as to which produced the largest change in predicted output.

A sensitivity analysis was conducted on the 12-node ANN model which produced the results seen in Figure 3.7a-b. As shown in the sensitivity analysis results presented in Table 4.1, almost all of the neighbor burn status nodes were highly sensitive to the 1.1 increase in value. Given what is known about the range of input data for those nodes, the results shown in Table 4.1 are understandable. NeuroSolutions normalizes all input data to a range

Table 4.1 *Sensitivity values for the training and test fires as shown in Figures 3.7a and 3.7b. See text for discussion.*

Nearest Neighbor and Type	Training Fires	First Test Fires	Second Test Fires	Sum
8bndy	8.57	9.95	6.62	25.14
2bndy	6.63	5.30	6.56	18.50
5bndy	4.04	4.69	4.94	13.68
1bndy	4.21	3.80	4.93	12.95
3bndy	3.22	2.89	4.53	10.64
6bndy	3.56	2.19	3.16	8.91
6absy	1.76	2.17	1.57	5.49
7bndy	1.68	1.97	1.79	5.44
1absy	1.50	1.77	1.19	4.47
7absy	1.21	1.89	1.09	4.19
5absy	1.13	2.19	0.77	4.08
0absy	1.30	1.94	0.68	3.92
2absy	1.24	1.43	1.10	3.77
3absy	1.24	1.45	0.93	3.62
8absy	1.03	1.81	0.74	3.59
4absy	1.02	1.74	0.76	3.52
2doq	1.15	0.63	1.44	3.22
5tm3a	1.11	0.70	1.09	2.90
1doq	1.06	1.21	0.50	2.77
6absx	0.82	1.19	0.69	2.70
4tm3	0.93	0.40	1.31	2.64
3doq	0.91	1.20	0.49	2.60
7tm4a	0.83	1.21	0.51	2.55
3tm3	0.80	0.89	0.62	2.30
5absx	0.70	1.09	0.49	2.29
6doq	0.68	0.45	1.13	2.26
4bndy	0.83	0.46	0.94	2.23
1tm7a	0.76	0.29	1.15	2.20
5tm7a	0.83	0.39	0.95	2.17
7tm4	0.76	0.58	0.82	2.16
8dem	0.80	0.59	0.75	2.14
5dem	0.78	0.43	0.92	2.13
7dem	0.70	0.39	1.00	2.10
4tm4a	0.86	0.37	0.81	2.05
1absx	0.76	0.84	0.45	2.04
0tm5a	0.68	0.93	0.36	1.97
4dem	0.72	0.24	0.99	1.96
5doq	0.61	0.37	0.97	1.95
4absx	0.57	1.03	0.33	1.94
2tm3a	0.71	0.49	0.74	1.94
8doq	0.61	0.67	0.59	1.87
2tm4a	0.54	0.72	0.59	1.85
6dem	0.62	0.52	0.71	1.85
7absx	0.70	0.52	0.62	1.84
3absx	0.67	0.77	0.38	1.81
7tm7	0.45	0.66	0.70	1.81
1wspd	0.35	0.85	0.55	1.75
0wspd	0.45	0.58	0.70	1.73
6tm7	0.69	0.44	0.60	1.73
7tm5	0.52	0.60	0.59	1.71
2tm5a	0.51	0.63	0.52	1.66
5tm3	0.65	0.62	0.39	1.65
2tm5	0.68	0.32	0.65	1.65
3tm4a	0.44	0.89	0.32	1.65
0dem	0.64	0.39	0.61	1.64
5tm4	0.73	0.19	0.69	1.62
4tm4	0.64	0.19	0.77	1.61
6tm3	0.54	0.53	0.51	1.59
0tm4a	0.49	0.71	0.39	1.59
4tm7a	0.59	0.28	0.70	1.58
7wspd	0.32	0.70	0.52	1.54
1tm5a	0.49	0.47	0.56	1.52
4wdir	0.42	0.54	0.55	1.50
3wdir	0.34	0.45	0.71	1.50
3dem	0.61	0.28	0.62	1.50

Key:

Training Fires = Anniversary, Busch, Cooperation, Fuelbreak
First Test Fires = Mile, Airport, Tuttle Marsh
Second Test Fires = ATV, Happy Hardwood, Powerline, Unhappy Camper

Nearest Neighbor Location

6	8	3
2	0	1
5	7	4

Nearest Neighbor Type
absx = absolute x distance from fire start
absy = absolute y distance from fire start
bndy = neighbor pixel burn status
dem = elevation
doq = digital orthophoto quarter quadrange
tmx = 10 May 1993 TM, where x = band number
tmxa = 25 August 1991TM, where x = band number
wspd = wind speed
wdir = wind direction

between the endpoints of the neuron type (e.g., 0 to 1 for sigmoid neurons) prior to their use in a network. For example, raw TM data would change in value from between 0 and 255 to a range between 0 and 1, with most of the values being either greater than 0 and less than 1. Since the burn status variable values are integer 0's and 1's, the normalization process does not change those values. Multiplying either the TM or burn status values by 0.1 would change each value equally, but the burn status pixels would have the greatest (and least) change overall.

Wildfire spread is a percolation process. Knowing the location of the fire front is very important in mechanistic models of fire spread (e.g., FARSITE). Given that knowledge of neighbor burn status is important information, it is reasonable to assume the network weights associated with those input nodes are of high predictive value and contribute strongly to the output. If the burn status pixels were unimportant in predicting a burn/no burn response, then the sensitivity analysis results (Table 4.1) would have reflected this. The sensitivity analysis produced a maximum amount of change for these inputs associated with weight values presumably among the largest in the network and, thus, they appear to be most sensitive. Even if the weights associated with the TM nodes equaled those of the burn status nodes, the 0.1 increase in burn status inputs would have an expected greater effect mathematically on the predicted output value.

In looking at maps of predicted burn patterns (e.g. Figure 3.7a-b), there are obvious interactions present between the known fire boundary, wind direction, and artifacts resulting from the queuing process. If the only, or most important, factor required by the network to predict a 0 or 1 output value was the known burn status of the nearest neighbors, then every pixel immediately adjacent to but outside of the known fire boundary would be expected to burn. Conversely, many interior pixels would have a no burn prediction since they are presented with nearest neighbor fire configurations similar to, and at a higher frequency than, the pixels just outside the known fire boundary. As shown in Figure 3.7a, neither of these scenarios is predominant, so the models are using other input data, in association with the neighbor burn status information, to accurately depicts overall burn pattern.

Approach #2

For this analysis, the input data files were modified to reflect a zero (0) value for each 14 input variables in sequence. Since there are 14 input variables for each of nine pixels (the predictor pixel and the eight nearest neighbor pixels) this involved "turning off" nine input nodes. Results are presented in Table 4.2. The four columns of numbers represent different performance measures. MSE is just the mean of the squared errors, NMSE is the mean squared error divided by the variance (which normalizes the MSE across various sized desired outputs). An NMSE less than 1 indicates a prediction better than predicting the mean each time (Euliano, pers. comm., 2000). The last two values, correlation coefficient (r) and percent error are best used together (high r and low percent error generally means a good performance by the network).

The first entry in the table show the performance of the 12-node model on the original training data collected during the final training (weight update) run. This represents the base value from which to compare other results. The next 14 entries represent the 12-node model response to having one of the various environmental variables "turned off" during a non-training (i.e., no weight changes occurred) run. For all by the neighbor pixel burn status (abcf_bndy) variable, the values were set to zero for the nine respective inputs. In the case of "abcf_bndy," since zero means "no burn" and one means "burn," the values were re-set to 0.5, essentially no signal one way or the other.

The model was relatively generic in it's (in)ability to handle the loss of signal from most input types, with a few, notable exceptions. Model prediction was essentially unaffected by removal of the absolute x/y distance. A relatively strong response was noticed when certain TM bands were not used, most notably Band 5 from the May scene (abcf_tm5), as well as Band 5 from the August scene (abcf_tm5a) and Band 3 from both scenes (abcf_tm3 and abcf_tm3a).

In addition to turning off individual signals, several other data alteration trials were conducted. The second set of entries in Table 4.2 reflect performance data from the individual fires used to train the 12-node model. From these results it appears that the sum of the four input fires (abcf_all_old) is greater than the parts, especially the Cooperation fire (coop_all_old). The third set of entries reflect model prediction performance when using averaged rather than raw data for some inputs. Some questions as the appropriateness of sampling nominally 30 meter data (i.e., TM and DEM coverages) at 10 meters without using some averaging routine were raised. To that end, the 30m TM and DEM coverages were converted to 10m grid size using the neighborhood mean process in ArcView with a 3x3 kernal.

In all cases, the original training and both test data sets, prediction accuracy decreased. As stated above, the meaning of these results is open to interpretation. One might consider just what the network is being told by "turning off" certain input signal channels. In the case of the nearest neighbor burn status (abcf_bndy), the input had to be changed to 0.5, because 0/1 mean something in the original training data. For the absolute x/y, DEM, DOQ, TM, wind speed and wind direction inputs, conversion to 0 just biases the network toward the "near zero" prediction range. Because as the input data are normalized to values between 0 and 1 prior to input, the environmental input variables whose values came out closer to 0 when normalized are now "represented" by the "turned off" (zero) inputs. In effect, we are telling the network that the inputs are closer to the lower end of the input range than the upper, and it is unknown how this affects the performance metrics. One method of addressing this question would involve running the same trials using one instead of zero (i.e., send a full signal instead of no signal). Also, similar to the burn status case, calculating the median value and using that as input might be an approach, but it is not quite the same case in that the number would represent the median-sized inputs, which is not a problem when all the inputs are either 0/1 as is the case for burn status. The mode would similarly favor those values, and a skewed distribution would bias the mean.

Standard sensitivity approaches deal with a fixed structure, which then is altered via parameter values within the model, feed in the same data, and test to see how the output changes. This tests the sensitivity of changes to the internal parameters. ANNs test for sensitivity to input changes, the dynamical aspects of the modeled environment. Once a standard model is calibrated, the structure is set and sensitivity is conducted using a fixed data set, which are now the structure in a test of model dynamics. Once an ANN is trained, the structure is fixed and cannot be altered in a meaningful way. So the training data are actually structural and the weights are dynamic. In a sensitivity analysis we are altering the input data (now the dynamic aspect of the model) and making the weights structural. In the final analysis, the sensitivity analysis method used by NeuroSolutions and presented above as Approach #1 seems to conform to traditional simulation model sensitivity analyses.

Fire Environment Variables and Scaling

The meso-scale approach for modeling wildfire as described in this document proposes and follows through on a very specific level of analysis. The primary assumption of "if fire starts today it will go somewhere" underlies the ANN fire modeling structure. Operationally, the decision as to whether this assumption is true for any given time-frame is necessarily made external to the ANN models and prior to sending a fire start location to the queuing program. Thus, the specified meso-scale ANN models are best placed within macro and micro-scale models that take into account processes operating at finer or broader scales. It is in these upper and lower level models that questions about current climate conditions, fuel moisture condition, and short-term and long-term precipitation totals would be addressed.

Broad-scale environmental variables such as AVHRR, early settlement vegetation, surficial geology, ownership and LTA were originally collected for, and some actually used in, ANN model development. Theses variables ultimately proved to be less useful as model inputs than originally thought, since their value did not change (or only two different values were present) within the spatial extent of the fires analyzed. ANN models are best developed with highly variable data. These variables were not providing a useful signal from which the network could generalize and were deleted from the input data vector because of this.

In contrast to almost all other wildfire spread models, an indicator of precipitation or fuel moisture was not used in these models. Fuel moisture is an important variable for micro-scale theory fire models, and precipitation regime is important to macro-scale fire modeling theory. Results presented in this document show that wind is an effective meso-scale variable for the climate leg of the fire environment triangle. Fuel moisture is very specific to fuel size class. Details of the spatial variation of these fuels cannot be known for modeling at meso-scales. Fuel moisture is a synthetic indicator of short-term rainfall and is too fine and fast a variable, as long-term precipitation average is too coarse and slow a variable for easy inclusion in this scale of model. Wind selects the next pixel to evaluate, the DEM and TM, along with wind, are used to predict burn probability.

Coda

As discussed in this document, the two general approaches to modeling wildfire spread patterns are fine-scale mechanistic or broad-scale probabilistic. Mechanistic approaches scale locally to what keeps a fire burning while fire spread in probabilistic models is constrained by the rate of percolation across the landscape. Changing spatial and temporal scales of fire environment variables lead to the inherent unpredictability found in middle number systems. Extant fire models lose predictive power when subtle shifts in environmental variables cause a qualitative change in fire behavior. Artificial neural networks (ANNs) are designed for problems with cross-scale relationships that produce non-linear changes in system behavior. Even though the system appears middle number, the ANN recasts system structure until, at an appropriate level of analysis, prediction becomes possible. The difficulty with ecological systems is they invite being cast as complex, and complex systems require different causal models. A systems approach incorporates the explanatory power of positive and negative feedbacks and the recognition of emergent system behavior. Because complex systems do not invite definitive answers, we need complex systems methodologies like ANNs to offer prediction with good explanatory power.

Within the defined level of analysis for these ANN fire models, wind speed and direction, the highly spatially variable information on fuels (contained in TM and DOQ spectral reflectance values), and elevation are the most appropriately scaled variables, given the goal and intended use of these models. The great reduction of this set of input variables is telling of other scales of fire modeling theory. Apparently, variables derived from primary data are presenting a very synthetic estimate of human understanding of what is present in the natural system. In the end, these synthetic classifications present mostly noise and confusion to the neural networks and, thus, are not useful in searching the relationship surface between inputs and outputs.

While this dissertation is ostensibly about developing a wildfire model, at its core it reflects more my interest in systems analysis and artificial neural networks. I hope that the future work this document spawns will continue the reassessment of tactics, questioning of assumptions, and elucidation of new strategies in approaching all types of ecological problems, not just wildfire. While I am certain that the ANN models presented here are not the be all and end all of fire modeling, I do think they are a vital bridge between fine-scale mechanistic and broad-scale probabilistic fire models. Meso-scale ANN models will take their place beside these other modeling approaches, expanding the available tools necessary to manage landscapes.

For this document, in keeping with accepted parlance and tradition, I have referred to the different fire modeling approaches in terms of scale (fine, meso and broad). However, I find it is more useful to think of extant fire models, and modeling in general, in terms of underlying theory. Fine-scale mechanistic models are essentially working from micro-theory, the pyrolysis of twigs in a simple, unvarying environment (*i.e.*, no wind, no slope). Broad-scale probabilistic models approach fire from a macro-theoretic standpoint, namely statistical distributions based on relatively long-term observations of environmental phenomena. ANNs are not restricted to meso-scale representations, but do provide a meso-theoretical modeling approach. It is the underlying theoretical approach that limits both mechanistic and probabilistic models, in the realm of fire spread and when seeking explanation of many other ecological problems. Our training as ecologists, and the conventions followed within a given paradigm, often lead us to try and solve problems from an inappropriate theoretical basis.

Much like Dupin's wonder at the police looking for a letter using a microscope. I wondered at the concept of analyzing burning landscapes using the pyrolysis of twigs as a foundation. I was not the first person to look at fire modeling and see that a blending of fine-scale and coarse-scale models had not been effective in addressing fire at meso-scales. But. identification of the issue. while important, was only the first half of the solution. As in Rosen (1981). redefining the strategy of meso-scale fire model development was the vital aspect that had not yet been effectively done. My hope is that this document is an effective and strategic redefinition of what it means to model wildfire using meso-theory.

5

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