On Developing a Meso-theoretical Viewpoint of Complex Systems by Exploring the Use of Artificial Neural Networks in Modeling Wildfires

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ABSTRACT

Modeling wildfire spread patterns is a complex problem involving long-term fuel accumulation (site history) with short-term thermodynamics. The two dominant approaches to modeling wildfire spread patterns are fine-scale and mechanistic or broad-scale and 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 fuel 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. This is usually a result of the fire environment scaling beyond the range of mechanistic fire spread equations or below the statistical power of regime calculations. Artificial neural networks (ANNs) are designed for problems with cross-scale relationships that produce nonlinear 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 use models like ANNs to offer prediction with good explanatory power without heavy data requirements and complicated module interactions. An ANN-based wildfire spread model was developed for the Great Lakes Region of the United States that integrates across scales of fire environment variables. Preliminary results support the proposed meso-theoretical fire environment definition and ANN-based modeling approach.

***Keywords and phrases*:** wildfire modelling, wildfire theory, complex systems, and artificial neural networks

1.0 INTRODUCTION

The results presented here continue from a previous work that outlined the theoretical aspects of meso-scale modeling in general, and proposed a specific approach to developing a meso-scale wildfire model (McCormick *et al.*, 2000). Readers are encouraged to review this previous work, as much background theory is not included here. This paper expands upon specific meso-scale model considerations by describing a generalized framework of meso-theoretical approaches to ecological modeling of complex systems. This document also outlines model development and testing methods, and presents some preliminary results.

1.1 Modeling and Middle Number Systems

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. Informal models guide us in developing research questions or making predictions such as how soon that thunderstorm will arrive to douse the fire in the barbeque pit. When informal observation is translated into logical, 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).

This paper is less an investigation into wildfire modeling and more an investigation of how modern ecologists approach the analysis of meso-scale processes with a certain strategic ineffectiveness. Specifically, the extensive literature on wildfire and wildfire modeling 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. 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 presented here is a strategic departure. While the specific discussions, arguments and examples contained herein concern wildfire, the sub-text is the use of ANNs to deal with middle-number systems. The focus is not the resultant model, it is how stepping outside of the limits of current models helps to model systems of great scale and high complexity.

1.2 An Introduction to 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." ANNs 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 by recognizing patterns in system variables. 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.

Conceptually, neural networks are quite simple and can be represented as graphs composed of a series of linked nodes that represent biological neurons and their connections. Multi-layer, feed-forward networks are acyclic and have a series of nodes arranged in layers (input, hidden and output), with links between every node in adjacent layers. 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. 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. 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.

There are two types of learning in neural networks, supervised and unsupervised. Unsupervised learning does not use target (output) data. For this study, fire burn patterns (target data) were available, so supervised training of the ANN fire models was possible. 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. 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.

1.3 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. Maissurow (1941) conducted one of the earliest studies of fire regime in the Great Lakes States, focusing on northern Wisconsin and adjacent lands in the Upper Peninsula of Michigan, USA. He concluded that 95% of the forests studied originated following fire disturbance. 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.

1.3.1 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 (1969) in Canada, and McArthur (1966, as reported in Baines, 1990) in Australia. 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, *et al.*, 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 (1983) 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, *et al.*, 1994). To compensate for certain of these limitations Finney (1996) used 17th Century Dutch mathematician Christian Huygens' principle of light wave propagation (French, *et al.*, 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 (Richards and Bryce, 1995).

1.3.2 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, *et al.*, 1994), percolation (Green, 1993), or contagion (Li and Apps, 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, *et al.*, 1990), nearest-neighbor movement rules (Bryant, *et al.*, 1993; Ratz, 1995) and invasive epidemic processes (Green, *et al.*, 1990).

1.4 Analysis of Extant Fire Modeling Approaches

Most wildfire models in use today (Rothermel, 1983; Andrews, 1986; Finney, 1993; Green, *et al.*, 1990; Clarke, *et al.*, 1994; Hargrove, *et al.*, 2000) operate by encoding endogenous fire processes (e.g., rate of spread). However, results from some fire spread models suggest that different, upper-level elements are controlling under varied environmental conditions (Green, *et al.*, 1990). Through repeated simulations these models can determine the degree to which a given landscape is connected, that is, able to sustain fire propagation, based on some critical threshold value (Green, 1994; Turner, *et al.*, 1989). Turner and Romme (1994) and others (Simard, 1991; McKenzie, *et al.*, 1996) discuss the need for a link between fine-scale mechanistic and broad-scale probabilistic wildfire models. They point directly to the essential need for model prediction of when synoptic weather, landscape pattern, or fire-line thermodynamics provides the more important constraint on wildfire spread.

In the preceding discussion I have focused on the fundamental aspects of no specific fire model, rather I have 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). Alternatively, fire regime and historical range of variation are powerful concepts for forest management, ecosystem assessment and system design (Swanson, *et al.*, 1994). However, 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.

Complex ecosystem models usually only incorporate two hierarchical levels (Holling, 1995). Stochastic modeling of fire regime sets intermediate variables of fuel and weather as the lower-level context. Alternatively, physically-based fire models code low-level, fast combustion processes, then scale-up to forest stands. Local anthropogenic alterations of the biosphere are now connecting globally, 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 produce a very complicated model. Also, while the details of a single process may be captured and encoded, details of cross-scale interactions of two separate processes may not be known or knowable.

2.0 STANDING AT THE CROSSROADS OF FIRE SCALE AND FIRE THEORY

A classification of fire models can take almost any form. 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. I have chosen the perspective that there are only two general wildfire spread model classifications: fine-scale mechanistic or broad-scale probabilistic. The crossroads referred to in the heading of this section 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 a 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).

Little substantive change in the general field of wildfire spread modeling has occurred in the last 30 years. 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). 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, *et al.*, 1999; Sessions, *et al.*, 1999; Keane, *et al.*, 1996). 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. McCormick, *et al.*, (2000) arrive at a similar conclusion. The problem with micro-theory and macro-theory models is that they seek to understand the *process of disturbance*, not necessarily predict well where 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.

3.0 MODELING WILDFIRE SPREAD PATTERNS

3.1 Wildfire Data Sets

Fire records for 11 fires that occurred during the summers of 1998 and 1999 on the Huron National Forest, Michigan, USA (Huron) were acquired. These records consisted of fire start location and a GPS-based fire perimeter, along with administrative details such as fire start time, stop time, date, cause (human-related or other), personnel and equipment used, and a cost analysis. Additionally, all readily available digital data were collected from the Huron Ranger districts the fires occurred on. The primary ecological and environmental variables collected for the area surrounding each fire include: Landsat TM imagery from 10 May 1993 and 25 August 1991; USGS 7.5 minute DEM data, Digital Orthophoto Quarter Quadrangle imagery; river/road locations; stand type and stocking density; ownership boundaries; ecological landtype associations (ELTs/LTAs); early settlement vegetation maps; classified land cover from AVHRR imagery; daily weather records from 1995 to 1999; and 30-year monthly climatic averages for precipitation and minimum and maximum temperature.

The primary significance of these data was their ready availability to fire management personnel on any forest ranger district in the Michigan, Wisconsin, or Minnesota. A main tenet of this modeling effort was to use data that did not require extraordinary effort to acquire (e.g., Keane, *et al.*, 1999). Spatial data sets were converted to a modified Albers Equal Area Conic projection. All digital 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. Vector coverages of the final fire perimeters were converted to 10 m raster coverages. A 10 m raster size was determined to best represent shape of smaller fire perimeters (e.g., Busch) while also minimizing the total number of pixels of the larger fires. In addition to these data, an x/y coordinate relative to the fire start coordinate was calculated for each pixel and used as input data.

3.2 Trials Using Data Subset By LTA

The known fire data were stratified into test data sets consisting of 72 and 28 percent of the total pixels in the evaluation area, which included the known burn area plus a surrounding buffer. Initial ANN models were developed using 28 percent of all the data from all 11 fires. After training, a single neural network was used to predict burn probabilities for the remaining 72 percent of all the fire data. Results for the 11 fires ranged between 86 to 95 percent accurate in making a “no burn” prediction for individual fires where there was no burn, and 90 to 99 percent for “burn” predictions. These results are quite good, but not unexpected. Since the 28 percent data set was stratified across the entire range of variation of the input data set, the ANN model had “seen” exemplars of all possible input combinations of the data type discussed in Section 3.1. Thus, there were no unexpected input vectors, and the ANN produced solid results for all the fires.

Five fires occurred within the same ecoregion, and presented the best chance of using a subset of data to train a network, and a second, independent subset to test the network. The five fires were named 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).

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. The networks were able to learn and predict quite well for the training data as shown in the top three fire maps in Figure 1. What both networks failed to do was predict with any accuracy for the test fires, as shown by the bottom two maps in Figure 1. From looking at the fire environment variable values, it was hypothesized that wind direction may be having an undue influence on prediction accuracy for these trials. The ABC fire complex had wind directions ranging from southwest to southeast whereas the FM data consisted of east and northeast winds. A new training subset was made of the ABCF fire data with only the Mile fire used for testing the network, as the wind direction for the Mile fire fell within the range of values for the ABCF fires.

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. While there were some networks that predict quite well, the overall results indicated that the networks were very sensitive to the initial random weight values and there were insufficient input exemplars to adequately adjust the weights. Furthermore, prediction in the upper quarter of the Mile fire changed significantly, but only outside the known fire boundary. From looking at the original data coverages, it was apparent the area north of the northern Mile 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 Huron property. So, while the prediction within the fire boundary remained good in many cases, once outside the known burned area the network was uncertain as to whether to start a fire or not. An alternative explanation is that the predictions within the fire boundary are actually poor, since the network was getting values of -1 (no data) at many of the input nodes 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 better than observed.

3.3 Altering Inputs To Improve Prediction

With no other changes in neural network topology possible, what were assessed to be minor environmental input variables were removed. The pruning of input data 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. 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 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. Approximately 100 network training 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 2). The Airport and Tuttle Marsh fires occur on the same subsection as the ABCFM fires but on different LTAs.

4.0 CONCLUDING DISCUSSION

The models developed to-date are supportive of the meso-scale fire modeling theory outlined above. 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 will spread to). Each input pixel knew the fire burn status of neighbor pixels. 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. However, 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. To develop a fully operational meso-scale ANN fire model several issues need to be addressed. As is evident from the results shown in Figure 2, accurate predictive fire models are possible using ANNs, and a fully operational model should produce output of similar accuracy. 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.

The ANN predicts a decimal burn probability estimate ranging from 0 to 1, but the networks were trained using integer values of 0 (no burn) or 1 (burn). 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. 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. Furthermore, decision rules that select between models would solve the problem of loss of predictive accuracy when crossing ecoregional boundaries (i.e., Airport and Tuttle Marsh fires, Figure 2). Neighborhood smoothing (e.g., majority filtering) could be used after an initial presentation of the queued pixels to a network.

4.1 Model Variables

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. These variables were not providing a useful signal from which the network could generalize and were subsequently deleted from the input data vector.

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-theory fire models, and climate/precipitation regime is important to macro-scale fire modeling theory. Results presented here 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.

4.2 Fire Models and Scale

The meso-theoretical 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.

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.

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, and allow for a meso-theoretical modeling approach.

It is the underlying theoretical approach that limits both mechanistic and probabilistic models, in the realm of fire spread modeling 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. 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.

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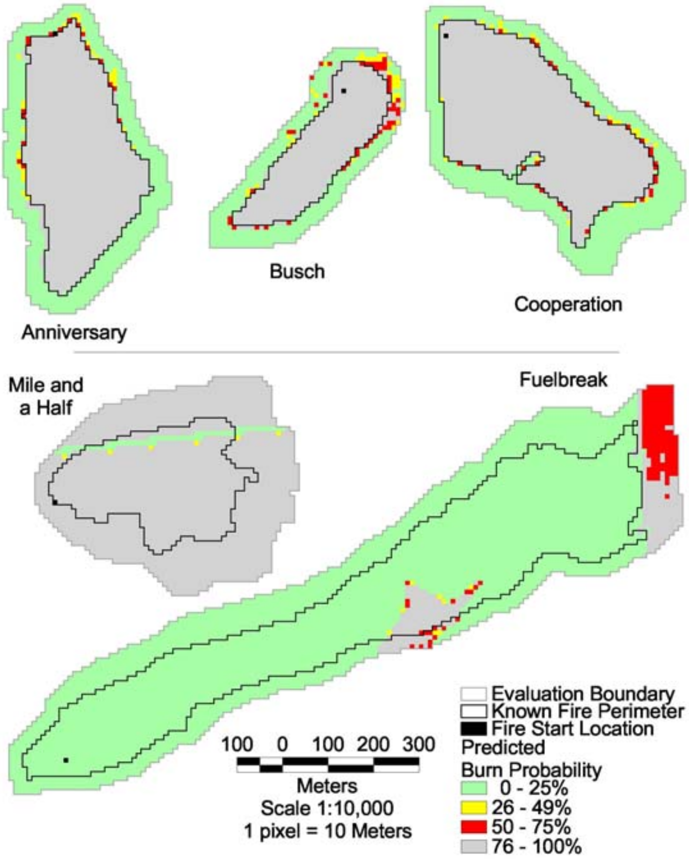

Figure 1. Predicted burn probability results for five fires on the Huron National Forest, Michigan, USA. Anniversary, Busch and Cooperation fire data were used to train a single ANN. The top three fire maps represent results from the final ANN training iteration, and the bottom two fire maps represent predicted burn/no burn status from the trained ANN. Gray or red within the known fire perimeter (black line) is "good" (predicted burn where burn occurred), while green or yellow outside the fire perimeter is "good" (predicted no burn where no burn occurred). While the final training run (top three maps) shows very good prediction, the test runs show almost complete failure of the model to distinguish burned versus unburned areas.

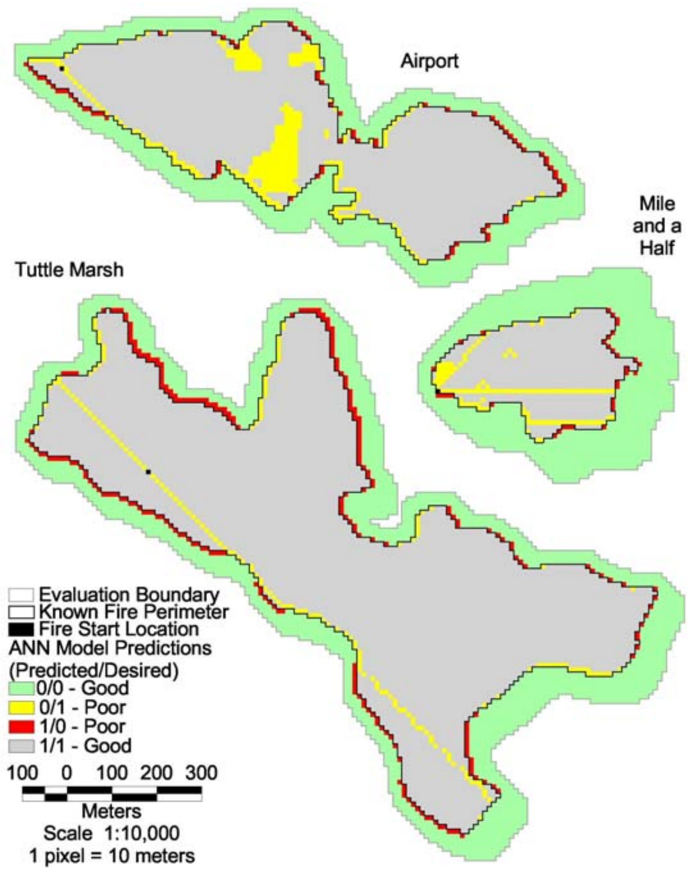

Figure 2. Final model prediction results for the Mile, Airport and Tuttle Marsh fires, using a trained 12-hidden node ANN with wind speed, wind direction, DOQ, DEM, TM and absolute x/y distance from fire start as inputs. Training fires were Anniversary, Busch, Cooperation, and Fuelbreak. The Mile fire occurred on the same landtype as the training fire, while the Airport and Tuttle Marsh fires occurred on different landtypes.