

# Review of Methods for Developing Probabilistic Risk Assessments. Part 1: Modeling Fire

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## Abstract

We describe methodologies currently in use or those under development containing features for estimating fire occurrence risk assessment. We describe two major categories of fire risk assessment tools: those that predict fire under current conditions, assuming that vegetation, climate, and the interactions between them and fire remain relatively similar to their condition during recent history, and those that anticipate changes in fire risk as climate and vegetation communities change through time. Three types of models have proven useful for predicting fire under current conditions: (1) biophysical models that predict fire from vegetation type, fuel load, and climate; (2) statistical models; and (3) fire behavior models. Programs such as LANDFIRE have great promise for using biophysical properties to estimate risk. Statistical models that use historical data to predict fire probabilities if landscape-fire relationships continue to remain relatively unchanged, are gaining interest as more data become available. Fire behavior models are producing accurate predictions of the ways individual fires will move across the landscape. For longer periods, fire risk needs to be evaluated by models that predict the ways vegetation communities will change over time because these changes will alter fire probabilities. We identified models capable of being used to track changes in vegetation and the resulting effect on changes in fire frequency. Risk systems need to be designed to track changes in fire susceptibility as the climate changes, using models such as MAPSS.

Prediction of fire occurrence is just the first part of a complete analysis of risks associated with fire. Fire occurrence risk needs to be combined with models that determine the risk of the effects of fire. Models that predict mortality, fuel consumption, smoke production, and soil heating

caused by prescribed fire or wildfire should be used, as well as those capable of evaluating second order effects, such as changes in site productivity, animal use, insects, and disease. Fire must be looked at in the context of other stresses, such as invasive insects and pathogens, encroaching urbanization, and loss of critical habitat. There are interactions among stresses that play a role in affecting the frequency and intensity of fire, and fire, in turn, can affect the probability of those stresses. Consequently, risk evaluation systems need to be created that can simultaneously estimate the probability of other major stresses influencing ecosystem development.

Keywords: Fire prediction, fire susceptibility, modeling, risk assessment, wildfire.

## Introduction

Methodologies are described here that may be useful for estimating fire occurrence risk assessment, including the probability of ignition and the spatial spread and intensity of the fire during its lifetime. Two types of risk need to be assessed: (1) fire risk occurrence (hereafter referred to as fire risk), and (2) risk to the ecosystem as a result of fire (hereafter ecosystem risk) (Finney 2005). For our purposes, fire risk includes the probability of ignition and the spatial spread and intensity of the fire during its lifetime. Ecosystem risk includes all of the consequences to plant and animal populations and to the soil during the recovery period once the fire has concluded. There is significant understanding of the factors that influence fire risk, with many studies analyzing the long-term consequences to ecosystems (Fairbrother and Turnley 2005). Tools to predict the likely distributional frequency of fire risk under combinations of various conditions are the focus of this review.

The two major categories of fire risk assessment tools are (1) those that predict fire under current conditions, assuming that vegetation, climate, and the interactions among them and fire remain relatively similar to their condition during recent history; and (2) those that anticipate changes in fire risk as climate and vegetation communities change through time.

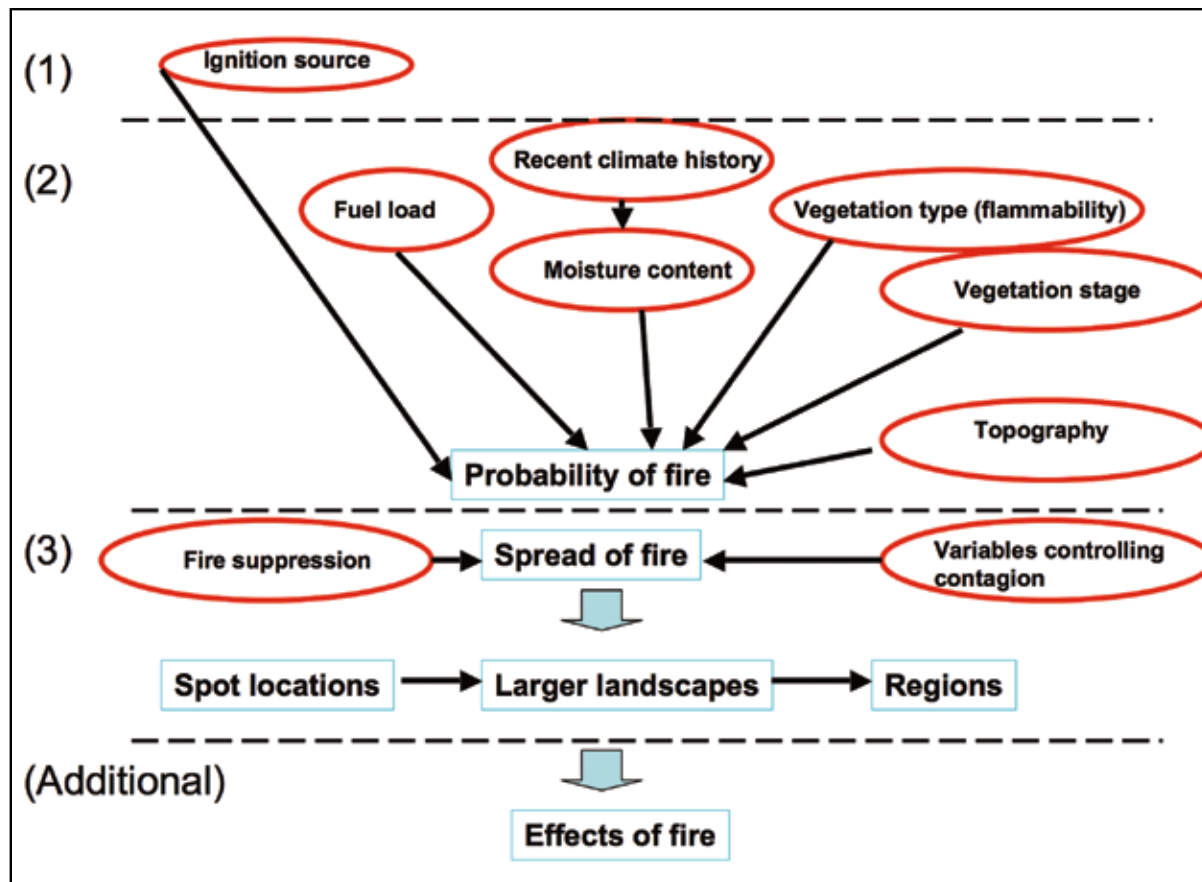


Figure 1—Calculation of fire risk. There are three aspects to predicting fire. Fire is predicted from (1) the probability of ignition; (2) the biophysical influences on fire, such as fuel load, moisture content, flammability of the vegetation, and topography; and (3) the spread of fire once it gets established. Effects of fire can then be calculated to form a complete estimation of the risks related to fire.

### Fire Risk under Current Conditions

Many models are available to evaluate fire risk under current conditions, although the majority of these were designed for analysis in specific locations or under specific sets of conditions. One of the initial attempts to implement a more generic assessment of fire risk was the National Fire Danger Rating System (Burgan 1988, Deeming and others 1972). This system relied on expert judgment to evaluate the risk from a set of explanatory variables, principally fuels, topography, and weather. It allowed land managers to estimate fire danger for today or tomorrow for a given rating area. It characterized fire danger by evaluating the approximate probable upper limit of fire behavior in a fire danger rating area during a 24-hour period. A relative rating of the potential growth and behavior of any wildfire was based on

a loose correlation between the date of fire discovery and the eventual size of a fire. Attempts to improve upon the National Fire Danger Rating System fall into one of three categories:

1. Biophysical models that predict fire from vegetation type, fuel load, and climate.
2. Statistical models that rely on relationships extracted from historical data.
3. Fire behavior models that emphasize the role of spatial distributions of wind, topography, and fuel in determining what portions of a landscape will burn.

As an example, the first and third of these can be combined in a fire risk calculation (shown in Figure 1) in which fire is predicted from the biophysical influences on fire and from the spread of fire once it gets established.

Biophysical models combine local weather patterns (temperature, humidity, wind), vegetation (fuel type, moisture level), and topography (elevation, slope) to arrive at an estimate of fire risk. Biophysical models range from deterministic models in which a given set of input variables will always yield the same prediction, to systems that include simulation. Some of these models combine quantitative and qualitative criteria to arrive at a fire danger index. Biophysical models designed to estimate fire risk across large regions tend to base their predictions on fewer variables because the number of variables that have been quantified across large regions is limited.

Statistical models use regression models developed from historical data to estimate probabilities of fire occurrence under various local environmental conditions. Statistical models are valuable for understanding general historical trends. They are used to provide predictions for such factors as the expected number of fires in an area from explanatory variables such as vegetation patterns, fuel moisture conditions, meteorological variables, number of people visiting a forest, and past history of fires. We describe these types of models only briefly because there are currently few published examples of statistical fire models available. However, the increasing availability of large historical data sets on fire frequency will undoubtedly cause a great expansion of studies using this method in the near future.

Fire behavior models attempt to characterize the propagation and spread of fires under various environmental conditions. Fire behavior probabilities are dependent on ignitions occurring off-site and the fuels, topography, weather, and relative fire direction allowing each fire to reach that location. Because these models require input variables that may not be available over large regions such as entire national forests, they tend to be applied to specific watersheds in which these properties have been mapped or quantified. Because there are many possible interactions of weather with spatial landscape features, fire behavior predictions require the use of spatial fire spread simulations.

To provide a sense of how the different types of approaches are applied and which resources each might require, we discuss in detail examples from each category. Biophysical models are first discussed, with particular

attention to two such systems, LANDFIRE and WALTER. Because LANDFIRE is the newest, and, perhaps, most complex approach being pursued, we discuss this approach in depth. WALTER is described as an example of an approach that makes extensive use of expert opinion. An example of the statistical modeling approach relying on large historical data sets is described with a discussion of a probability-based model. Finally, we discuss a suite of fire behavior models—FARSITE, BehavePlus, FlamMap, NEXUS, and Visualized Fire Simulation (VFS).

### **Fire Risk under Changing Vegetation or Climate**

Many models have been constructed with capabilities of projecting changes in vegetation composition over time and the way these changes alter fire risk (Keane and others 2004). Other models are capable of simulating how changes in climate will change biological processes and interactions in ecosystems. Slow changes in vegetation or climate or both can be incorporated into the fire risk calculation using these models. Recent reviews (Keane and others 2003) have concluded that simulation modeling produces the best predictive ability under changing climate and vegetation conditions compared to prediction based on either biophysical properties or statistical prediction from historical data. Over longer time periods, climate and vegetation change is very likely to occur.

We discuss the advantages of these models, building on the extensive evaluations of succession fire models (Keane and others 2004). Further, we attempt to place the models they considered in the context of a wider range of tools. We discuss the four most widely used succession models that contain processes that link vegetation change to fire prediction: SIMPPLLE, MAGIS, VDDT, and TELSA. Many other available models perform well for specific locations for which they were designed. We focused on these four because they have the potential to be easily applied to many different areas in the Western United States.

A final category of simulators includes those that utilize broad concepts of biological processes to project the ways forests are likely to change and where various forest types are likely to be found under future climate conditions. Although this type of model has had a long history

of development in forest ecology, it is only recently that several models have had fire intimately incorporated into the model structure. We describe the MAPSS model as an example of this category.

## Biophysical Fire Risk Systems

Biophysical fire risk models traditionally use regional characteristics of weather patterns (temperature, humidity, wind), vegetation (fuel type, moisture level), and topography (elevation, slope) to produce a prediction index of fire risk based on historical correlations among these variables and fire. More recently, models are being developed that substitute spatial simulations for some of these correlations.

## LANDFIRE

In response to a need for a national evaluation of the spatial distribution of fire risk, the USDA Forest Service developed a partnership with four other agencies to develop LANDFIRE (<http://www.landfire.gov/index.html>). The goal of LANDFIRE is to identify areas at risk because of the accumulation of hazardous fuel for the purpose of prioritizing hazardous fuel reduction projects and improving hazardous fuel treatment coordination between agencies. The program is designed to produce landscape-scale maps and data describing vegetation, fire, and fuel characteristics across the United States (at a 30-m grid resolution) (Keane and others 2004, Rollins and others 2002, 2004; Schmidt and others 2002). LANDFIRE is providing many of the raw materials that will be necessary to produce an estimate of fire risk. Although it is not yet in general use or publicly available, it is important to discuss it here because of the key role LANDFIRE will play in fire risk assessment over the next decade.

The spatial distribution of potential vegetation, existing vegetation, canopy height, and canopy cover is mapped using gradient-based field inventories coupled with gradient modeling, remote sensing, ecosystem simulation, and statistical analyses. Biophysical gradient maps have been created containing 38 geographical information system (GIS) layers describing the direct and indirect conditions affecting the distribution of vegetation and fire regimes

(Figure 2). The vegetation of the continental United States is divided into approximately 500 biophysical units, based on plant composition and the Ecological Systems categorization (<http://www.natureserve.org/>). Each successional stage of each biophysical type is separately tracked. Fuel models are assigned to each mapping region, producing fuel maps for fire behavior models, canopy fuel projections, and fuel characterization classes. Crown bulk density and height to crown base are calculated at the plot level from tree lists.

Inputs consist of coarse-scale, 1-km<sup>2</sup> resolution, spatial data layers. These include potential natural vegetation type, current cover type, site characteristics (such as soils, climate, and topography), historical natural fire regime (fire frequency and severity), and Fire Regime Current Condition Class (layer depicting the degree of departure from historical fire regimes). There are three additional databases that are used as input:

1. National Fire Occurrence—Federal and non-Federal fire occurrences from 1986 to 1996.
2. Potential Fire Characteristics—the number of days of high or extreme fire danger calculated from 8 years of historical National Fire Danger Rating System (NFDRS) data.
3. Wildland Fire Risk to Flammable Structures—the potential risk of wildland fire burning flammable structures based on an integration of population density, fuel, and weather spatial data.

Landscape characteristics that are used to determine fire occurrence and behavior include height to crown base, crown bulk density, fuel loadings, cover type, percentage cover, height for each of the forest, shrub, and herbaceous layers, and an estimate of the departure from reference normal fire regime condition class. The interaction between these characteristics and fire probability is estimated by using a suite of computer models, WXFIRE, BIOME-BGC, LANDSUMv4, FARSITE, and HRVStat, discussed in the next section.

LANDFIRE produces three fire regime maps:

1. Simulated historical fire frequency and severity.
2. Fire regime condition class (FRCC).
3. Indices of departure from reference conditions.

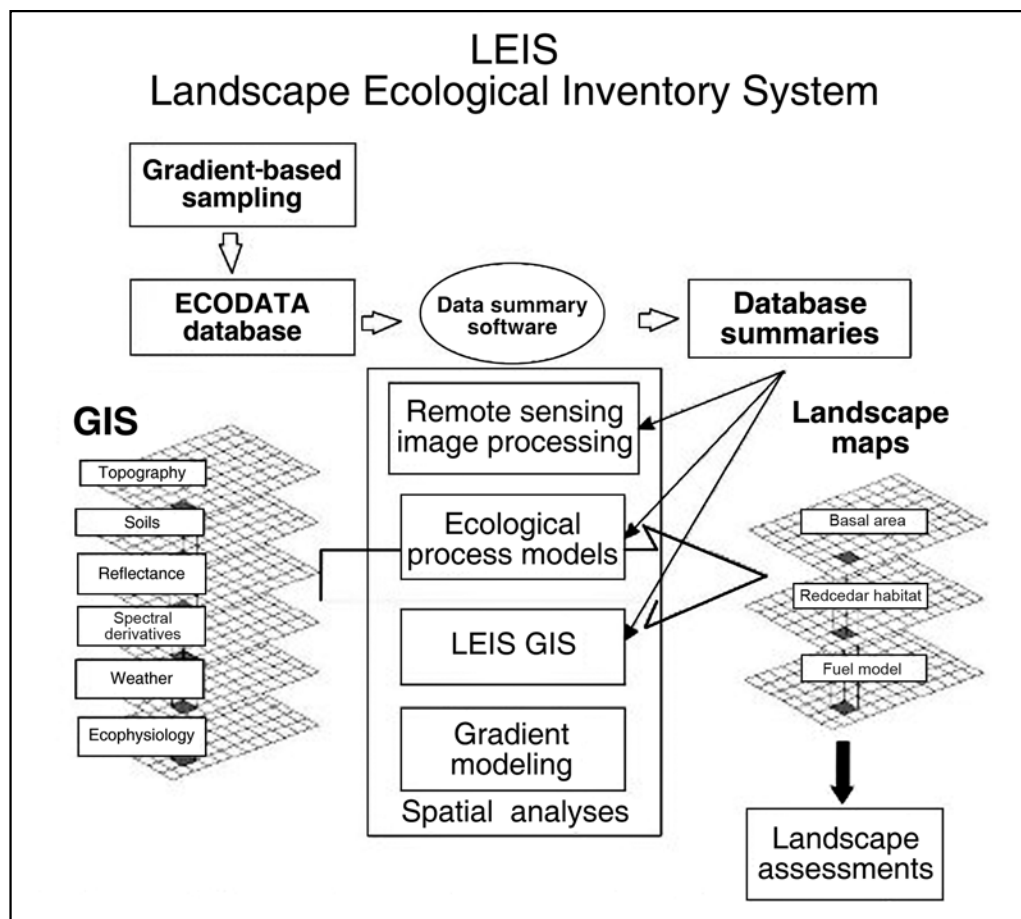


Figure 2—A diagram of the Landscape Ecosystem Inventory System used by LANDFIRE. Boxes in the center represent the steps used to create the ECODATA database, the LEIS GIS, and landscape planning maps. Initial and derived GIS layers (left side) are used as independent variables to predict maps of landscape and ecosystem characteristics (right side) for landscape assessments and ecosystem management (Keane and others 2002).

These tools are used for determining the degree to which current landscape conditions have departed from historical reference condition vegetation, fuel, and disturbance regimes. Figure 3 shows an example map of fire regime condition classes produced by LANDFIRE. An example map of reference fire regimes is shown in Figure 4.

The data layers being produced by LANDFIRE will provide basic information from which a risk assessment can be calculated. However, there are drawbacks to this system. LANDFIRE'S classifications of fire conditions may be too coarse. The calculation of probabilities may require data on a continuous scale. Further, it is not clear whether this data is sufficient to predict the average likelihood of a fire at a

location or the distribution probabilities of fires of different sizes and intensities. The probability of a worst-case scenario would be difficult to estimate from LANDFIRE'S products.

Because the past condition and fire susceptibility had much to do with past climate, it is unclear whether LANDFIRE will correctly predict the relationship between vegetation, fuel loadings, and fire that will be shaped by future climates. LANDFIRE places less emphasis on the importance of the heterogeneity of types of fire and the key differences among these types, such as crown fires vs. ground fires. LANDFIRE focuses on classes that are relevant to management and current vegetation classifications. There may be advantages to having the flexibility to

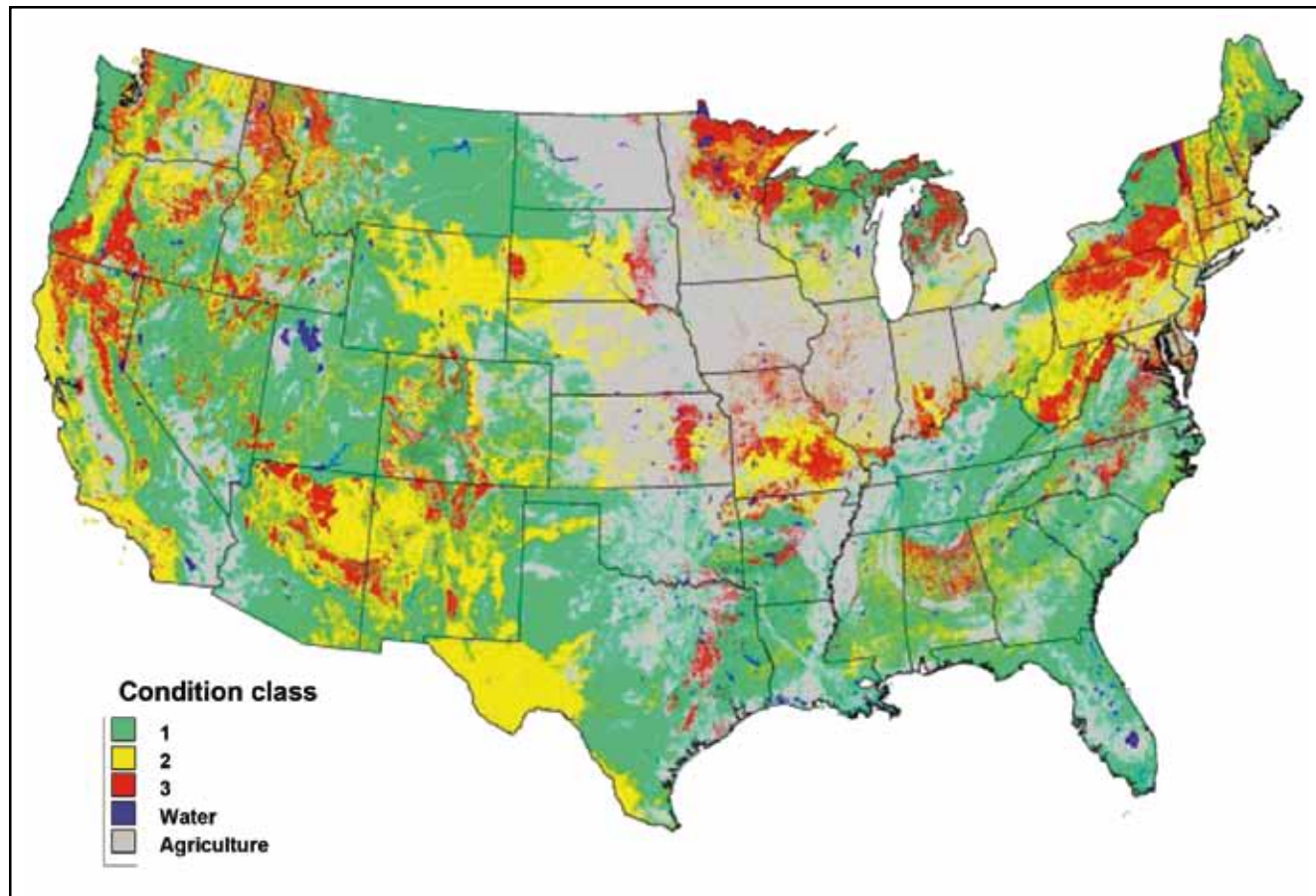


Figure 3—LANDFIRE National Fire Regime Condition Class Map, 2002, Missoula Fire Sciences Laboratory (Hann and others 2004, Hann and Bunnell 2001, Schmidt and others 2002). Conditions 1 (low risk, forest regimes are within their historical range, shown in green), 2 (moderate risk, forest regimes are moderately altered from their historical range, shown in yellow), and 3 (high risk, forest regimes are significantly altered from their historical range, shown in red).

make changes in these classifications. Natural variability in landscape and fire characteristics, and their influence on fire (and the uncertainty with which predictions can be based on these characteristics) is not treated implicitly within the system.

#### **LANDFIRE Models—**

WXFIRE (Keane and Holsinger 2006) computes spatially explicit, climate-based biophysical variables at any landscape scale or resolution using daily weather data, topography, and soils parameters, and a diverse set of integrated environmental functions. WXFIRE computes over 50 biophysical attributes such as potential evapo-transpiration for each simulation unit. The user must estimate all input parameters for each simulation unit to create an input file to WXFIRE. WXFIRE then calculates, record by record,

all biophysical attributes by accessing the DAYMET spatial weather database (Thornton and others 1997) (<http://www.daymet.org>) and using the daily weather to compute important climate and ecosystem biophysical variables. The DAYMET database consists of 18 years of daily temperature, humidity, radiation, and precipitation estimates at a 1-km spatial resolution for the contiguous United States. Output from WXFIRE can be used to digitally map those ecosystem characteristics needed by land management including fire regime, fuel load, and vegetation cover type.

BIOME-BGC (Thornton and others 2002) is used to calculate expected forest productivity in response to a given set of environmental conditions. BIOME-BGC is an ecosystem process model that simulates carbon, water, energy, and nitrogen budgets for both vegetation and soil.



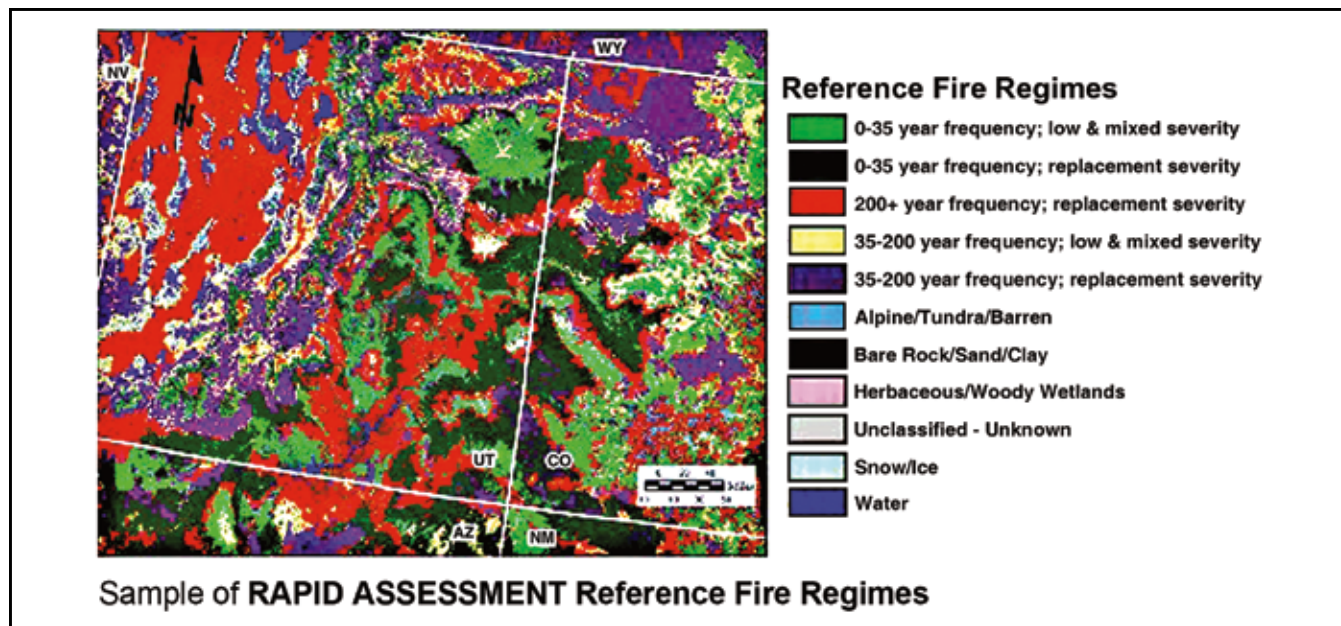


Figure 4—LANDFIRE rapid assessment reference fire regimes. The figure identifies the locations with fire regimes with a 0 to 35-, 35 to 200-, and greater than 200-year frequency and replacement severities ranging from low and mixed to replacement. Also identified are locations of alpine, bare rock, wetland, snow/ice, water, and unclassified landforms. (<http://www.landfire.gov/RA2Image.html>; Updated map <http://www.landfire.gov/RA3Image.html>).

BIOME-BGC is inherently non-spatial and can be run on an area of any size: a single point, a watershed, a continent. BIOME-BGC computes a set of carbon and water budget metrics on a daily time step driven by daily weather data such as gross primary production, net primary production, evapo-transpiration, and runoff. The model requires three types of information as input: site physical characteristics, plant physiological characteristics, and daily weather data. A set of generic plant functional type (PFT) ecophysiological parameter files has been developed from the literature for use with BIOME-BGC (White and others 2000). The PFTs include evergreen needle leaf forest, deciduous broadleaf forest, evergreen broadleaf forest, deciduous needle leaf forest, evergreen shrub, c3grass, and c4grass.

The range and variation of historical landscape dynamics are estimated with LANDSUMv4 (Landscape Succession Model version 4.0) and HRVStat (Historical Range and Variation Statistics) of landscape characteristics (Keane and Holsinger 2006, Keane and others 2002). LANDSUMv4 simulates fire and succession on fine-scale landscapes for land management applications. Species composition and stand structure are assumed to change at a predefined rate,

although disturbance initiation is modeled stochastically, and disturbance effects are based on the current vegetation conditions.

The model FARSITE projects the spread of fire across landscapes, using slope relationships and wind vectors (discussed separately under the fire behavior model heading). FIREHARM (<http://ams.confex.com/ams/pdfpapers/66069.pdf>) is used by LANDFIRE to produce probabilities of a given fire event from long-term weather. It identifies areas of highest risk based on fuel consumption, smoke production, tree mortality, soil heating, crown fire index, and proximity to urban areas. FIREHARM will produce a probability of fire for each category of weather conditions (i.e., the number of days the fire potential is above a certain level). FIREHARM will calculate four fire behavior variables (fireline intensity, spread rate, flame length, crown fire potential), five fire danger variables (spread component, burning index, energy release component, Keetch-Byram drought index, ignition component), and five fire effects variables (smoke, fuel consumption, soil heating, tree mortality, scorch height) for every day in the DAYMET 18-year record for each spatial location. The program will simulate

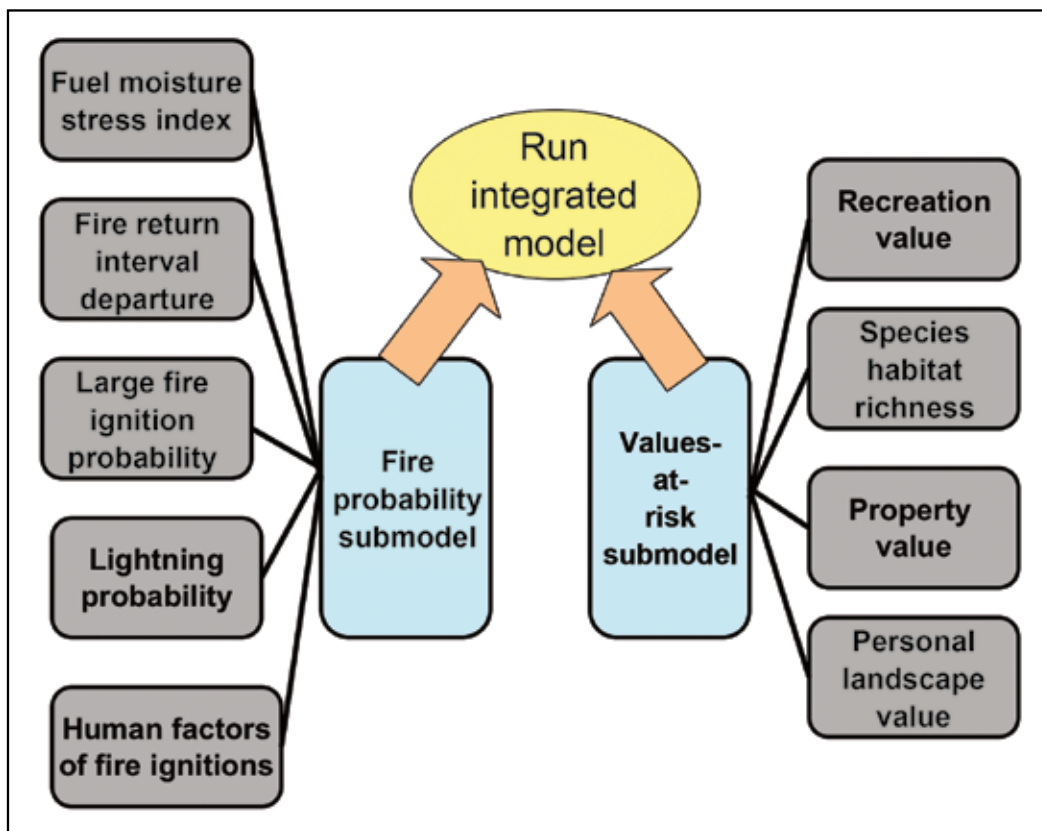


Figure 5—Components of the Fire-Climate-Society Model in Wildfire Alternatives (WALTER), showing the principal processes integrated into the full model analysis. (Adapted from <http://java.arid.arizona.edu/ahp/>).

moisture conditions for each dead fuel component (e.g., duff, litter, downed woody, logs) and live fuel component (e.g., shrubs, herbs, trees) using a complex set of biophysical equations.

### Wildfire Alternatives (WALTER) (FCS model)

The Wildfire Alternatives (WALTER; <http://walter.arizona.edu/index.asp>) system for estimating fire risk is being developed at the University of Arizona. It is an interdisciplinary research initiative aimed at improving our understanding of the processes and consequences of interactions among wildfire, climate, and society. WALTER seeks to capitalize on advances in geospatial, analytical, and Web delivery technology to provide access to scientific research activities and findings and educational materials using the decision support tool, Fire-Climate-Society Strategic Fire Model (FCS-1).

FCS-1 is an online, spatially explicit strategic wildfire planning model with an embedded multi-criteria decision process that facilitates the construction of user-designed fire risk assessment maps for different climates (Figure 5). The resulting maps show spatially explicit information about the geographical distribution of fire probability and values at risk for the selected study area.

FCS-1 was developed for the varying vegetation, climate, and topography as well as the unique human dimensions of wildfire found in southeastern Arizona and northern New Mexico. The model currently is made up of five fire probability and four values-at-risk model components. FCS-1 can be run under differing climate and corresponding fuel moisture conditions. Through an analytical hierarchy process, FCS-1 allows users to assign weights to individual model components. The online application



can be used to help understand differing views and build consensus.

Like many expert systems, WALTER has the framework for considering an array of disparate factors in evaluating the ways they may influence fire. However, expert opinion can have uncertain predictive ability. The main value of this type of system is to identify interrelationships that may require management to control fire frequency and pattern.

### **Expected Net Value Change**

A model has been developed for calculating the expected net value change (ENVC) as the product of the probability of a fire at a specific location and the resulting change in financial or ecological value (Finney and others 2007). The model calculates the sum of the product of the probability of the *i*-th fire behavior at a specific location over *N* fires multiplied by the benefits and losses afforded for the *j*-th value of *M* values received from the *i*-th fire behavior. The expected net value change (ENVC) can include financial, ecological, or other values at present day or future discounted values. Assumptions about the effect of wildfire suppression on wildfire probability and value change can also be incorporated into the (ENVC) equation. The estimation of wildfire probabilities for a specific future period is derived from a calculation of the minimum travel time a hypothetical fire would take moving across the landscape, using algorithms from the FARSITE fire behavior model (discussed under the "Fire Behavior Modeling" heading). These models are run in parallel using a set of networked computers and an estimate of the spatial pattern of forest vegetation and fuels.

This model has been applied to a 16 000-ha wildland-urban interface in eastern Oregon simulating 12 fuel management scenarios and four land value schemes. Burn probabilities were estimated by simulating 200 randomly ignited wildfires, and then the average net value change for each fire and pixel on the landscape was estimated. The results indicate that fuel reduction on a relatively minor percentage of the landscape (20 percent) resulted in a 20-percent to 50-percent positive change in ENVC for most of the scenarios simulated.

### **Probability-Based Fire Statistical Models**

Probability-based fire risk models (Brillinger and others 2006) defined risk using three probabilities:

1. The probability of fire occurrence.
2. The conditional probability of a large fire assuming an ignition occurs.
3. The unconditional probability of a large fire.

An illustration of the general approach shared by these types of models is the probability-based fire risk model (Preisler and others 2004), which estimates fire probability by fitting a nonparametric logistic regression to data grouped in cells of 1 km<sup>2</sup> with a temporal resolution of 1 day. The input used by this model is:

1. The probability of fire occurrence (historical data).
2. The conditional probability of a large fire given ignition (daily values of precipitation, lightning, temperature, windspeed, and humidity).
3. The unconditional probability of a large fire (10-hour lag fuel moisture).

It produces maps of predicted probabilities and estimates of the total number of expected fires in a given region and time period. This method is particularly useful for assessing the utility of explanatory variables, such as fire, weather, and danger indices for predicting fire risk. It has the advantage of basing fire predictions on rigorous use of probability statistics.

### **Fire Behavior Modeling**

Fire behavior models predict the propagation of fire by assuming that the landscape is subdivided into cells, and each cell has a probability of burning that depends on conditions in the cell and in surrounding cells (e.g., Beer 1991). Many of these models use a deterministic version of the elliptical growth model (Green and others 1983, Richards 2000) to simulate spread of forest fires. The input data for these models include a base vegetation map, which can be generated with a vegetation simulator, such as Forest Vegetation Simulator (FVS) (Dixon 2002) and a fuel load simulator, such as Fuels and Fire Extension (<http://www.essa.com/downloads/prognosis/ffe.pdf>). Fire behavior

predictors were initially built for local-scale projections, where initial ignitions and spatial distribution of landscape properties could be precisely specified.

Among the more widely applied fire behavior models is FARSITE, which predicts fire spread and intensity across a specific landscape as a continuous fire over multiple time steps at a user-specified resolution, commonly 30 m. The focus of FARSITE is to simulate fire growth and the changes that occur over time for a specific fire. It uses spatial information on topography and fuels along with weather and wind files to simulate surface fire, crown fire, spotting, postfrontal combustion, and fire acceleration. FARSITE requires spatial landscape information from a GIS to run, including slope, aspect, surface fuel, canopy cover, crown base height, crown bulk density, and stand height. The outputs include a prediction of fire perimeter length and location, spread rate, intensity, flame length, and heat per unit area. Although the focus is on a single fire, a regional prediction could be made by combining output from all fires each year. Fire spread predictions are based on a snapshot of current vegetation structure. In order to simulate fire behavior under future conditions, the changes that will occur in the vegetation structure must be known.

BehavePlus (<http://fire.org/>) predicts fire behavior based on fuels, weather, topography, and wildfire situations. BehavePlus uses a minimum amount of site-specific input data to predict fire behavior for a point in time and space (i.e., spatially explicit data layers are not used). The present version of BehavePlus simulates only surface fire spread, but later versions may include crown fire simulation capability.

FlamMap (<http://fire.org/>) is a fire behavior mapping and analysis program, based in a geographic information system (GIS) that computes potential fire behavior characteristics (spread rate, flame length, fireline intensity, etc.) over an entire FARSITE landscape for constant weather and fuel moisture conditions. FlamMap uses spatial information on topography and fuels to calculate fire behavior characteristics at one point in time, assuming that all cells in the landscape function independently of one another. A map is produced for an area of any modeled value, such

as fuel moisture, fireline intensity, scorch height, or fuel consumption. Comparisons can be made between locations, or the effect of fuel treatment can be examined.

NEXUS (<http://fire.org/>) is an Excel spreadsheet linking surface and crown fire prediction models to compute indices of relative crown fire potential. NEXUS is useful for evaluating alternative treatments for reducing crown fire risk and assessing the potential for crown fire activity. NEXUS includes several visual tools useful in understanding how surface and crown fire models interact.

VFS (<http://fire.org/>) is a graphical user interface-(GUI-) based computer program to simulate and animate fire on heterogeneous landscapes. VFS captures fire spread behaviors based on fuel configuration, wind regime and topographical effects using percolation algorithms such as static percolation, depth first search recursive algorithm, and dynamic percolation with fire front. Users can compare the simulation capability of each method (e.g., burned pattern maps). Furthermore, output from VFS can be linked to GIS and used to cross-validate other fire simulation models. To evaluate the sensitivity of the input parameters of each method, users can specify a range for each parameter in VFS and test the influence of changes in parameters on model predictions. VFS can be used as a parameterization tool for the forest landscape models that incorporate fire spread simulation.

## Models to Estimate Effect of Vegetation Change on Fire Risk

Fire risk over long periods cannot be adequately evaluated without projecting the ways that the structure and composition of forest vegetation and fuels will change over time. Fire is very sensitive to vegetation structure and composition (Clark 1993, Swetnam 1997, Swetnam and Baisan 1996). Fire will, in turn, affect the rate and direction of vegetation change (Lenihan and others 1998).

Keane and colleagues classified 44 linked fire succession models, based on their complexity, principal mechanism, and stochasticity in their simulation design (Keane and others 2004). Most of these models fall into the category of fire behavior models because they attempt to simulate, at a fine scale, the dynamics that cause fire to

**Table 1—Model selection key for selecting the most appropriate linked fire succession models for fire management and research applications**

Criteria	Models
Management application	
Limited computer resources, modeling expertise, and/or input data available	
Fire pattern important	
Support and documentation available	TELSA
Not as above	LANDSUM
Fire pattern NOT important	
Support and documentation available	FFE-FVS
Not as above	SIMPPLLE, FETM
Abundant computer resources, modeling expertise, and/or input data available	
Individual tree or species processes important	
Support and documentation available	None
Not as above	LANDIS, QLAND, FIN-LANDIS
Only stand level characteristics important	
Support and documentation available	LANDMINE, SELES
Not as above	BFOLDS, CAFE, DISPATCH, EMBYR, INTELAND, LADS, LANDSIM, RMLANDS, SAFE- FOREST, SEM-LAND
Research application	
Explore climate, vegetation, and fire dynamics	
Coarse-scale applications	BFOLDS, BIOME-BGC, CENTURY, MC-FIRE, GLOB-FIR
Landscape-scale applications	
Individual tree or species-level processes important	
Fire pattern important	FIRE-BGC, LAMOS, SIERRA
Not as above	DRYADES, ZELIG-L, ZELIG-B
Only stand-level characteristics important	
Fire pattern important	MAQUIS, FIRESCAPE
Not as above	REG-FIRM
Explore fire and vegetation dynamics	
Coarse-scale applications	ALFRESCO, FIREPAT
Landscape-scale applications	
Individual tree-level processes important	
Fire pattern important	FIN-LANDIS, LANDIS
Not as above	None
Only stand level characteristics important	
Fire pattern important	ANTON, CAF' E, DISPATCH, EMBYR, INTELAND, LANDSIM, MAQUIS, MOSAIC, QTIP, RATZ, RMLANDS, SELES, SEM- LAND, SUFF2
Not as above	BANKSIA, FLAP-X, ON-FIRE, SUFF1, SUFF2, VASL

Source: Keane and others 2004.

spread across a landscape. These authors provide a handy table for deciding which models to use based on (1) whether

the purpose is management or research, (2) the importance of predicting fire patterns, (3) whether information is

needed on specific species or just on stand characteristics, and (4) what spatial scale is of interest (Table 1).

Complex models such as Fire-BGC (Keane and others 1989) and LANDIS (Mladenoff 2004, Mladenoff and others 1996) simulate vegetation change as a complex function of either the development of nutrient cycling conditions or the driving force of individual life history characteristics. The most complex of these are the gap models such as ZELIG-SP (Miller and Urban 1999) that predict successional development by simulating the dynamics of each individual tree on representative plots in the forest. Simpler models, such as SIMPPLLE (Chew and others 2004), represent vegetation changes as a predictable succession of stages following a resetting disturbance. We have selected a few of these models that are in common use for further discussion below.

### SIMPPLLE and MAGIS

SIMPPLLE (SIMulating Vegetative Patterns and Processes at Landscape scaLEs) is a stochastic non-spatial simulation model for projecting vegetative change over time in the presence of natural processes, either with or without management treatments. It models interaction of various natural processes on a landscape. Because it is stochastic, multiple simulations are run to generate a record of the frequency of natural disturbances for each polygon in the landscape. These frequencies represent an estimate of the risk of these natural processes occurring over a given period of time and are used to develop a risk index for each section of the landscape.

MAGIS (Multiple-resource Analysis and Geographic Information System (<http://www.fs.fed.us/rm/econ/magis/>)) is a spatial decision-support system for using the risk index to find optimal management practices spatially and temporally for a landscape. MAGIS uses optimization to select the spatial arrangement and timing of treatments that fit user-determined objectives and constraints. A variety of resource effects, management targets, and economic costs or benefits can be used to specify the objective and constraints for scheduling both vegetation treatments and road activities.

With these two programs, the user can evaluate a variety of management alternatives. However, their projections

are dependent on the estimate of current fuel distributions across the landscape. When projecting into the future, they will be increasingly in error as these fuel loads change.

### Vegetation Disturbance Dynamics Tool

Vegetation Disturbance Dynamics Tool (VDDT) (<http://www.essa.com/downloads/vddt/>) was developed to support the Interior Columbia River Basin Assessment. This nonspatial tool uses a state-and-transition matrix approach to predict changes in vegetative composition and structure using disturbance probabilities and successional pathways, including infrequent large-scale disturbances such as stand-replacement fires.

VDDT models typically apply to potential vegetation types. For each of these types, succession classes are defined according to the cover type and structural stage. In the absence of disturbance, vegetation community assemblage changes from one succession class to the next. Both natural and man-caused disturbances that affect vegetation can be examined. In VDDT, disturbances are defined for each succession class according to type (e.g., wildland fire, harvest, etc.), succession class destination, probability of occurrence, and the relative ages for which each probability applies. For each year of the simulation, VDDT determines whether each landscape unit is subjected to a disturbance.

### Tool for Exploratory Landscape Scenario Analyses

Tool for Exploratory Landscape Scenario Analyses (TELSA) (<http://www.essa.com/downloads/telsa/index.htm>) is a spatially explicit extension to VDDT that simulates forest succession, natural disturbances, and forest management activities. It is designed to simulate up to 250 000-ha landscape units. TELSAs can be used to simulate multiple scenarios, each characterized by different assumptions about management actions and natural disturbances. Because wildfires and other natural disturbance events that affect vegetation dynamics are inherently unpredictable, the model can use multiple stochastic simulations of each scenario to provide estimates of the mean, range, and variability of the selected performance indicators. Unlike

many other strategic planning models of landscape dynamics, TELSA takes into account natural disturbances so users can explore how their proposed management strategies will interact with vegetation succession and disturbances to alter landscape composition and structure. This model has been used to define the transition times between various succession classes (combinations of species composition and structural stage), the probabilities and impacts of disturbance by insects, fire or other agents, and the impacts of landscape management actions on structure and composition.

### **Models to Estimate the Effect of Climate Change on Fire Risk**

Biophysical process models can be used to estimate the effect of vegetation change on fire risk. The representation of basic processes in biophysical process models allows them to project the consequences of known relationships under future conditions. These models are capable of examining the effects of long-term changes in conditions such as climate change. An example of these model types, MAPSS (<http://www.fs.fed.us/pnw/corvallis/mdr/mapss/>) predicts vegetation distributions from either the availability of water in relation to transpirational demands or the availability of energy for growth (Neilson and Wullstein 1983, Neilson and others 1989, Stephenson 1990, Woodward and Williams 1987).

MAPSS and its recent derivative, MAPSS-CENTURY1 (MC1), simulate life-form mixtures and vegetation types, fire disturbance, and ecosystem fluxes of carbon, nitrogen, and water (Lenihan and others 2003). MC1 is routinely implemented on spatial data grids of varying resolution (i.e., grid cell sizes ranging from 900 m<sup>2</sup> to 2500 km<sup>2</sup>) where the model is run separately for each grid cell (i.e., there is no exchange of information across cells) (Bachelet and others 2000, 2001; Daly and others 2000). MAPSS has been implemented at a 10-km resolution over the continental United States and at a 0.5-degree resolution globally (Neilson 1993, 1995; Neilson and Marks 1994). It has also been implemented at the watershed scale (MAPSS-W, 200-m resolution) through integration with a distributed catchment hydrology model (Daly and others 1994, Wigmosta and others 1994).

Using climate data at a monthly time step, the model calculates the leaf area index (LAI) of three generic life form groups—trees, shrubs, and grasses—in competition for both light and water given a site water balance consistent with observed runoff (Neilson 1995). Water in the surface soil layer is apportioned to the two life forms in relation to their relative LAIs and stomatal conductance.

MAPSS is used to develop midterm forecasts of fire risk by using spatially distributed, high-resolution climate data and potential future climate forecasts from climate models. An example of these predictions is given in Figure 6. The PRISM model (<http://www.ocs.orst.edu/prism>) is used to produce high-resolution data grids of observed fire weather extending back to 1895 and interpolations of weather station data that are sensitive to topography. Fire risk forecasts, including fire occurrence, area burned, and fire behavior are generated from the historical and forecast weather data (Bachelet and others 2000, Lenihan and others 2003) (<http://www.fs.fed.us/pnw/corvallis/mdr/mapss/pubs.html>). A fire event is triggered in any given cell on any day if one of three thresholds is exceeded. A threshold of the 12-month standardized precipitation index (SPI) is used as an indicator of moderate to severe drought to control the inter-annual timing of fire events. A threshold of the 1,000-hour fuel moisture content of dead fuels is used as an indicator of extreme fire potential to control the seasonal timing of fire events. A threshold of fine fuel flammability is used as an indicator of the sustainability of fire starts to control the timing of fire events at the daily time step. There is no constraint on fire occurrence by the availability of an ignition source, such as lightning or human-caused ignition. Once a fire event is triggered, the MC1 fire module determines the fraction of each cell burned, which is dependent on the current vegetation type, the current drought condition, and the number of years since fire.

Potential fire behavior is also influenced by estimates of the mass, vertical structure, and moisture content of several live and dead fuel size-classes. The consumption of aboveground biomass, carbon, and nitrogen stocks are simulated as a function of the moisture content of each live and dead fuel size-class and the vertical structure of the canopy. The more rapidly growing grasses are assumed to



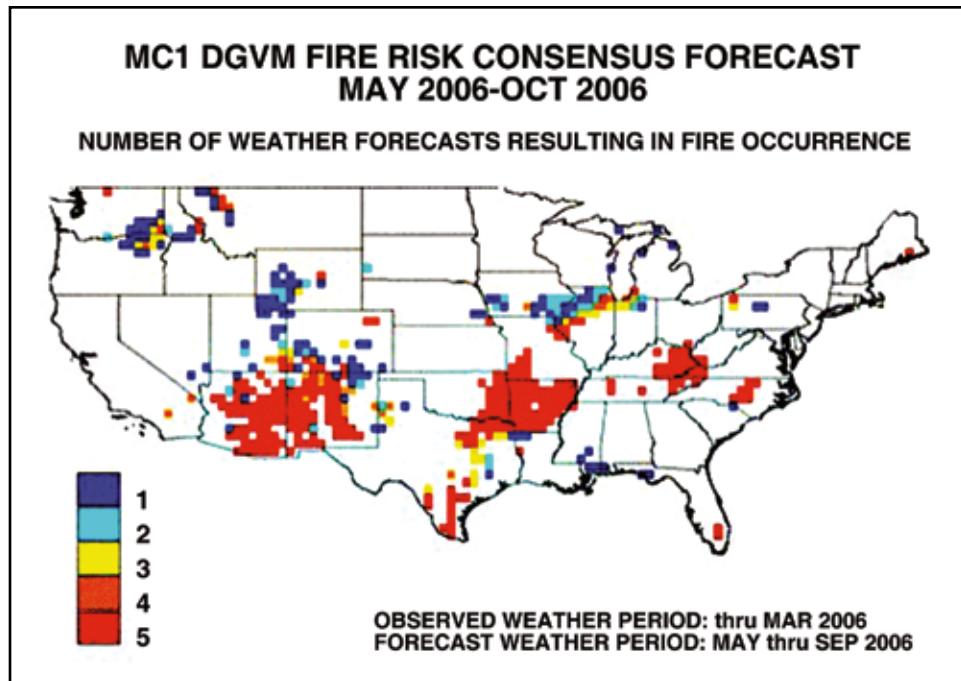


Figure 6—MAPSS simulation of fire probability MC1 DGVM fire risk consensus forecast, May to October 2006. The map shows the locations where from one (blue) to five (red) weather forecasts resulted in a fire occurrence (<http://www.fs.fed.us/pnw/corvallis/mdr/mapss/GRAPHICS/CONSENSUS>).

gain an advantage over woody life forms in the competition for water and nutrients, promoting even greater grass production which, in turn, produces a more flammable fuel-bed and more frequent fire. MAPSS is capable of producing predictions of future vegetation change and fire risk over a large geographical area.

## Conclusions Concerning the Use of Fire Modeling Systems

Much effort has gone into creating a capability of predicting fires throughout the region, both in their likely location and frequency. We described two major categories of fire risk assessment tools: those that predict fire under current conditions, assuming that vegetation, climate, and the interactions between them and fire remain relatively similar to their condition during recent history; and those that anticipate changes in fire risk as climate and vegetation communities change through time. Three types of models have proven useful for predicting fire under current conditions:

1. Biophysical models that predict fire from vegetation type, fuel load, and climate.
2. Statistical models that use historical data to predict fire probabilities if landscape-fire relationships continue to remain relatively unchanged.
3. Fire behavior models that produce predictions of the ways individual fires will move across the landscape.

Programs such as LANDFIRE have great promise for using biophysical properties to estimate risk. The LANDFIRE program is creating base data sets of fuel loadings, biophysical variables, and vegetation composition. Risk assessments conducted with LANDFIRE tools will depend heavily on well-tested models such as FARSITE. Since the intention is to implement the LANDFIRE project nationally at a fine-scale resolution, its data sets could provide the framework around which to build other risk evaluations. However, the data sets produced by LANDFIRE could be made even more valuable if they contained information on

the probabilities of fires of different sizes, intensities, and heterogeneity of fire types at any given location.

For longer periods, fire risk must be evaluated by models that predict the ways vegetation communities will change over time because these changes will alter fire probabilities. Risk systems must be designed to track changes in fire susceptibility as climate changes, using models such as MAPSS. LANDFIRE is not currently designed to track these changes, so it is unclear whether it will correctly predict the relationship between vegetation, fuel loadings, and fire that will be shaped by future climates. MAPSS would have a much higher likelihood of being able to track these changes in relationships.

Prediction of fire occurrence is just the first part of a complete analysis of fire risk. Fire occurrence risk must be combined with models that determine the risk of the effects of fire. For example, one such effects model is FOFEM (a First Order Fire Effects Model) (<http://fire.org/>), which predicts mortality, fuel consumption, smoke production, and soil heating caused by prescribed fire or wildfire. It uses an algorithm key that selects different functions for different geographic areas and cover types. It can be used for setting acceptable upper and lower fuel moistures for conducting prescribed burns, determining the number of acres that may be burned on a given day without exceeding particulate emission limits, assessing effects of wildfire, developing timber salvage guidelines following wildfire, and comparing expected outcomes of alternative actions. There are second-order effects, such as changes in site productivity, animal use, insects, and disease that need to be evaluated by other models.

Fire must be looked at in the context of other stresses, such as invasive insects and pathogens, encroaching urbanization, and loss of critical habitat. There are interactions among stresses that play a large role in affecting the frequency and intensity of fire, and fire, in turn, can affect the probability of those stresses. Fire probability can increase in stands that have experienced large amounts of tree mortality caused by native pest infestations. Because these precursor stresses have received less attention than fire, the uncertainty for predicting their probability is much

higher. The effects of fire are dramatic, but its role in shaping the future of forest systems may be equaled or exceeded by other stresses. Consequently, it is vitally important that risk evaluation systems be created that can simultaneously estimate the probability of all the major stresses influencing forest and grassland development.

In the development of fire modeling systems, data sets containing fine-scale grids of key data on the landscape have been established, with most containing detailed information on variables such as fuel loads, vegetation, and climate trends. These variables are likely to be useful in evaluations of many other kinds of risks. LANDFIRE'S classifications of fire conditions may be too coarse and inflexible to be useable to assess risks across a number of stresses at a given location. Vegetation mapping systems being developed (Kerns and Ohmann 2004, Ohmann and Gregory 2002, Wimberly and Ohmann 2004) may provide a much more flexible solution to this problem. Although there is not yet a movement toward a standard set of spatial data where models require identical inputs, such standardization could certainly aid risk comparisons. However, in order to compare fire risks to those from other threats, a flexible classification of forest types may be needed that is not just centered on fire risk characteristics.

The great proliferation of fire modeling systems in different portions of the regions suggests that each has specific strengths in simulating fires in the area for which the model was originally designed. However, maintaining so many different types of models in the fire modeling toolbox will inevitably prove unwieldy and confusing to potential users. Consequently, an effort toward consolidation (or choice of the best models) is likely to occur. The ultimate question is whether any of the tools discussed above could provide an initial framework on which evaluations of risks to other threats could be added. The best models would be those that facilitate comparison between fire risk and its associated ecosystem risk and the risk from other threats. It was not possible in this manuscript to evaluate which fire models offer a better route for considering multiple interacting stresses. This question must remain a primary one to consider in the choice and use of models.

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