THE SPATIAL CONTEXT OF FIRE: A NEW APPROACH FOR PREDICTING FIRE OCCURRENCE

Carol Miller
University of Montana, School of Forestry, Missoula, MT 59812, and Aldo Leopold Wilderness Research Institute, USDA Forest Service, Rocky Mountain Research Station, P.O. Box 8089, Missoula, MT 59807

ABSTRACT

Across North America, decades of fire suppression and recent patterns of human settlement have combined to increase the risks that wildland fires pose to human life, property, and natural resource values. Various methods can be used to reduce fuel hazards and mitigate these risks, but funding and other constraints require that these fuel treatments be prioritized across large landscapes. An understanding of where fire is most likely to occur on the landscape would allow managers to strategically prioritize their fuel hazard reduction efforts and to design effective fire management plans.

Predictive models of the probability of burning can be developed using empirical relationships between landscape variables and historic fire data, but this approach is limited to areas with extensive records of historical fires. Furthermore, models that are empirically derived from landscape variables have low predictability because fire spread is a spatially contagious process; the probability of any location burning depends primarily on whether neighboring locations are likely to burn.

This spatial context of fire occurrence can be addressed with a more mechanistic modeling approach. In this paper, I present a modeling approach whereby a map of the probability of burning is derived using information on the spatial distribution of fuels, topography, and ignitions. This approach uses generally available spatial data, climate information, standard geographic information system functions, and equations that describe the physics of fire spread. The potential use and application of the approach are discussed, and its performance is evaluated via a qualitative comparison with 20th-century fire occurrence data from the Selway-Bitterroot Wilderness in northern Idaho and western Montana.

keywords: fire frequency, fire history, geographic information systems, Idaho, Montana, probability of burning, Selway-Bitterroot Wilderness, spatial model.

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INTRODUCTION

A major focus of fire science research is to develop an understanding of where and when wildfires are most likely to occur. Timing and locations of ignitions have been examined (van Wagtendonk 1993, Garcia et al. 1995, Knapp 1998) and patterns of fire frequencies have provided general guidance for wildland fire management (van Wagtendonk 1986, McKelvey and Busse 1996). Although these efforts have contributed to our general knowledge of fire, today's management challenges require a more sophisticated understanding. Land managers require a site-specific understanding of fire occurrence for effective scheduling, planning, and allocation of resources to fire and fuels management activities. An improved understanding of fire-occurrence patterns would also provide valuable insights to research scientists about the factors influencing fire regimes and the dynamics of fire-dependent ecosystems. In this paper, I describe a new approach for predicting the probability of burning that has utility for management and research purposes.

Spatial data on historical fire occurrence have enormous potential to help improve our understanding of fire regimes, and geographic information system (GIS) technology provides the means to utilize these data (e.g., Chou et al. 1990). Logistic regression and multiple regression have been used to develop predictive models of fire occurrence (Chou et al. 1993, McKelvey and Busse 1996, Chang 1999, Rollins 2000), classification and regression tree analysis has been used to identify important relationships between fire occurrence and a variety of environmental variables (Rollins 2000), and multi-scale analyses have shown that the importance of variables can shift with the scale of observation (Chang 1999). While results from these kinds of studies have advanced our understanding of fire regimes, they are inadequate for providing a predictive model for managers because factors such as elevation, topographic position, and vegetation type explain only a minor portion of the variability in fire occurrence. Instead, the variable that is most important for predicting whether a particular location is going to burn is the number of neighboring locations that burn (Chou et al. 1993, Chang 1999). This finding is intuitive: fire spreads, and as a contagious process, the spatial context of fire is extremely important in describing or predicting patterns of burning. Furthermore, these statistical approaches require large data sets and therefore are limited to areas having extensive data on previous fire history.

A mechanistic approach based on the variables known to affect the process of fire spread may be better suited for predicting probability of burning, and unlike a statistical approach, can be applied to areas lacking fire history data. In addition, a mechanistic approach can explicitly address the spatial context of fire. This paper describes a modeling approach that utilizes GIS to predict the probability of burning for every location on a landscape. The approach is a practical one that relies on available data and builds upon our existing knowledge of fire occurrence, fire behavior, and fire weather. The model is demonstrated for the Selway-Bitterroot Wilderness and is evaluated via a qualitative comparison with 20th-century fire data for the area.

STUDY AREA

The 1.2 million-acre (0.5 Mha) Selway-Bitterroot Wilderness (SBW) is located on the border of north-central Idaho and western Montana (46°N, 115°W). The climate ranges from inland-maritime in the northwestern part of the SBW to a continental rainshadow climate in the southern and eastern portions (Finklin 1983). Average annual precipitation ranges from less than 65 cm at the lowest and driest sites to 200 cm at higher elevations. The fire season typically runs from late June to mid-September; during this time, lightning-caused fires accompany frequent thunderstorms. The vegetation in the SBW ranges from open stands of ponderosa pine (*Pinus ponderosa*) at lower elevations, to mixed-conifer forests at intermediate elevations, to whitebark pine (*Pinus albicaulis*), alpine larch (*Larix lyallii*), and Engelmann spruce (*Picea engelmannii*) at higher elevations (Habeck 1976). The area experiences a mixed-severity fire regime: many fires are nonlethal surface fires but under suitable weather and fuel conditions, lethal surface fires and even stand-replacing crown fires occur (Brown et al. 1994). Within the wilderness boundary, unplanned ignitions are usually allowed to burn, although if a threat is perceived to the wildland–urban interface outside the wilderness, fires within the wilderness are controlled (Law et al. 1997).

MODEL DESCRIPTION

Waiting Time Probability

The following methods were developed to estimate the probability of burning for every pixel on a raster landscape. The approach follows the same logic in the fire management application tool RERAP (Rare Event Risk Assessment Program), which estimates the likelihood that a fire will threaten a designated geographic location or point of concern before a fire-stopping weather event (i.e., precipitation) will occur (FRAMES 2003). Whereas RERAP is used to perform a nonspatial analysis for a single fire incident, the modeling approach described in this paper represents a translation of this concept to a spatially explicit landscape for multiple possible fire incidents occurring over time periods ranging from years to decades.

Fire travels through space and time from an ignition source to a target point. Whether or not the fire reaches the target point depends upon 1) the time required for fire to travel the distance from the ignition to the target, and 2) the time that elapses before a fire-stopping weather event (e.g., a heavy rain) occurs. The probability that a fire-stopping weather event occurs within the time required for fire to travel the distance can be estimated from historical weather data and the cumulative distribution form of the Weibull function (Latham and Rothermel 1993, Wiitala and Carlton 1994):

$$prob_{stop} = 1 - \exp\left[-\left(\frac{w}{\sigma}\right)^{\eta}\right], \qquad (1)$$

where w is the time required for fire to travel from the ignition to the target, and σ and η are parameters estimated from a least-squares fit to the cumulative distribution of annual waiting times for fire-stopping weather events. The probability that a fire-stopping weather event does *not* occur within the time period w is equivalent to the probability that the fire does indeed reach the point of concern, or

$$prob_{burn} = 1 - prob_{stop} = \exp\left[-\left(\frac{w}{\sigma}\right)^{\eta}\right]. \qquad (2)$$

The Weibull function has been used in individual fire assessments but to translate this approach to an entire landscape and to a temporal scale that is relevant for planning (i.e., years to decades), these parameters must be reinterpreted. To apply the Weibull function to these larger temporal and spatial scales, w is interpreted for every point on a landscape as the time it takes for fire to spread to it from an ignition point, and σ and η can be estimated across a landscape from the distribution of annual fire season lengths.

To compute this probability, several spatial data layers must be derived: ignition probability density, the time required for fire to spread from an ignition to any point on the landscape, and the length of the fire season, from which the parameters σ and η can then be determined. The derivation of each of these three layers is described below. Several existing modeling tools were used to generate the intermediate information needed to implement this approach, including Fire Family Plus (Main et al. 1990); FARSITE (Finney 1994, 1995); and FlamMap (M. Finney, U.S. Forest Service Fire Sciences Lab, unpublished model). AMLs (Advanced Macro Language) were used in ARC/INFO (ESRI 1998) to manipulate and derive the appropriate spatial information described below.

Ignition

While any particular ignition event may at first seem to occur in a random location, analysis of spatial ignition patterns over several years can reveal areas on the landscape where fires are more likely to start. Locations of fire starts caused by both anthropogenic and natural sources during 1970–1994 were obtained for the area encompassing the Selway-Bitterroot Wilderness from the National Interagency Fire Management Integrated Database and imported as a point coverage to ARC/INFO. From 1970 to 1985, these data report

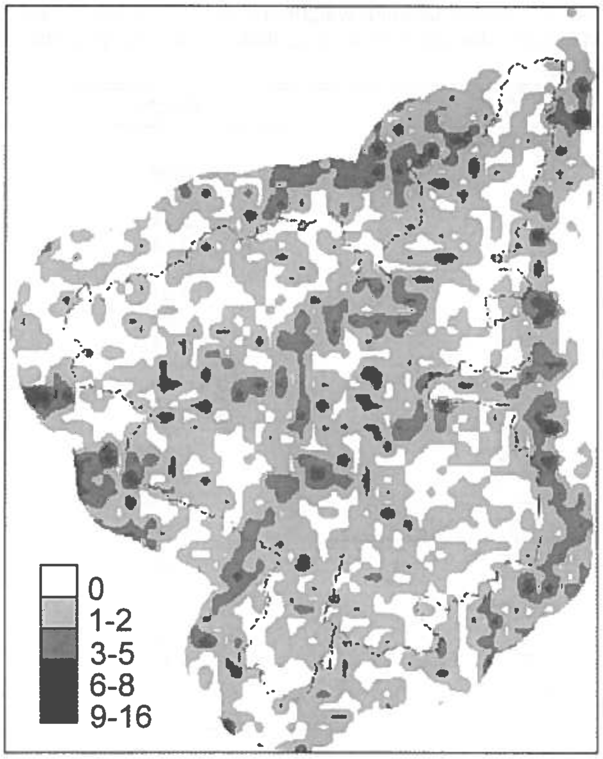

Fig. 1. Ignition density as number of ignitions in 25 years (1970–1994) in the Selway-Bitterroot Wilderness, Idaho and Montana.

the fire-start location to the nearest township–range location and therefore are very coarse spatial estimates. From 1986 to 1994, the data have a finer resolution because they report latitude and longitude. I combined both sets of data using the POINTSTATS function in ARC/INFO to aggregate the number of fire starts into 2000 × 2000-m cells. This coarse grid was then resampled to a resolution of 120 m using the ARC/INFO RESAMPLE function with bilinear interpolation.

Four ignition-density maps were created from this density surface corresponding to four categories of ignition occurrence for the 25 years of data: 1–2, 3–5, 6–8, and 9–16 ignitions (Figure 1).

Spread Time

Historical weather, rate of spread calculations, and the PATHDISTANCE function in ARC/INFO GRID (ESRI 1998) were used to compute the time required for fire to spread to any grid cell in the study area from an ignition source (i.e., w in Equation 2). Ignition sources were defined by each of the four ignition-density maps described above.

Historical Weather

Twenty-five years (1970–1994) of daily weather observations for May through November from seven weather stations in the area were imported into FireFamilyPlus (FFP) (Main et al. 1990). FFP was then used to generate a daily list of the recorded weather data, fuel moisture values, and the Spread Component (SC) index. I classified these records into 8 categories according to SC percentile and calculated the mean values for each variable in each percentile category (Table 1).

Rate of Spread

The modeling tool FlamMap (M. Finney, U.S. Forest Service Fire Sciences Lab, unpublished model) produces expected fire behavior values at every cell on a raster landscape. The program requires spatial inputs for fuels and topography from a GIS in raster form, whereas weather variables are input in a non-spatial fashion. The program uses the same landscape files and file formats required for the fire behavior simulation model FARSITE (Finney 1994, 1995), which contain information on topography and fuels for the area. FlamMap also requires information on fuel moisture, and although this must be initialized as uniform across the raster landscape, the user has the option to subsequently condition fuel moisture by solar exposure and weather. When this user option is invoked, FlamMap uses the same weather files required for FARSITE simulations.

I used FlamMap to generate 8 separate raster maps of rate of spread representing the 8 different weather conditions in Table 1. The mean fuel moisture values in Table 1 were loaded into 8 fuel moisture files (*.FMS) using FARSITE, and these files were used to initialize the fuel moistures in FlamMap. Similarly, 8 weather definition files (*.WWD) were generated in FARSITE from the mean values of temperature, humidity, rain, and wind speed in Table 1. I assumed that daily minimum temperature and maximum humidity occurred at 0500 hours and that maximum temperature and minimum humidity occurred at 1400 hours, and created week-long weather-scenario files (*.WTR). These weather-scenario files were used to condition the fuel moistures in FlamMap so that spatial variation from topographic effects on fuel moisture could be simulated. Inputs for fuels and topography were obtained from Keane et al. (1998).

Cumulative Spread Time

The rate of spread output from FlamMap, ignition-density maps, and the ARC/INFO PATHDISTANCE function were used to determine w, the time for fire to reach each point on the landscape. First, the rate-of-spread values for each raster cell were transformed to units of time by dividing the cell size (120 m) by the rate of spread. Grid cells with rate of spread equal to zero were considered to be unburnable and impenetrable to fire spread. The PATHDISTANCE function was then used to compute the cumulative spread time from every cell to the nearest ignition source. This function calculates, for each cell, the least-accumulative-cost distance over a cost surface from a source cell or a set of source cells. The function also compensates for horizontal factors, such as wind, that influence the total cost of moving from one location to another. In the application described here, the cost surfaces were the 8 spread-time grids (transformed from rate of spread),

Table 1. Summary of weather data from seven weather stations in Idaho and Montana[a] for 1970–1994.

Percentile category	Spread component	Fuel moisture (%)					Temperature (°C)		Relative humidity (%)		Rain (mm)	Wind speed (km/h)
		1-hr	10-hr	100-hr	Live herb	Live wood	Minimum	Maximum	Minimum	Maximum		
0–25	1.304	24.94	26.74	20.06	143.17	152.47	4.96	17.71	50.17	97.81	5.334	4.86
25–50	3.963	10.8	14.0	16.3	143.04	153.65	5.06	23.15	34.94	96.00	1.041	5.71
50–75	5.382	8.38	12.2	15.3	112.41	134.77	5.37	24.74	31.75	93.87	0.406	6.42
75–90	6.761	7.28	10.99	14.65	83.61	115.59	4.64	24.75	28.89	91.06	0.356	6.76
90–95	8.346	6.32	9.81	13.69	71.85	105.36	5.17	26.08	24.97	87.77	0.152	8.06
95–97	9.338	6.21	9.19	13.39	67.37	100.23	5.41	26.70	24.64	87.15	0.127	9.00
97–99	10.645	5.60	8.64	12.91	66.21	98.46	6.05	27.77	22.46	85.43	0.051	10.30
99–100	14.612	5.39	8.28	12.33	67.63	98.41	6.92	27.71	21.62	82.77	0.152	14.12

[a] Names and locations of weather stations: Fenn (46.100°N, 115.535°W); Hells Half Acre (45.636°N, 114.618°W); Moose Creek (46.118°N, 114.903°W); Powell (46.500°N, 114.667°W); Chair Point (45.467°N, 116.218°W); Red River RAWS (45.702°N, 115.334°W); West Fork (45.818°N, 114.263°W).

Table 2. Values used for weighted averaging of wind, weather, and ignition classes in final computation of annual probability of burning.

Class	Weight
Wind direction	
N	0.09
NE	0.05
E	0.04
SE	0.04
S	0.12
SW	0.31
W	0.26
NW	0.09
Weather percentile	
0–25	0.25
25–50	0.25
50–75	0.25
75–90	0.15
90–95	0.05
95–97	0.02
97–99	0.02
99–100	0.01
Ignition density	
1–2	0.05
3–5	0.14
6–8	0.26
9–16	0.41

and the source cells were as described by the 4 ignition density maps. Eight different wind directions were considered separately as horizontal factors in the function. The cumulative spread time was computed for each combination of the 4 ignition density maps, 8 spread-time grids (representing 8 weather types), and 8 wind directions. I then computed a weighted average of the cumulative spread time for the 8 different wind directions using the weights given in Table 2. These weights were based on the frequency of occurrence in the 25 years of weather data. After this weighted averaging, there were 32 different maps of cumulative spread time representing each combination of 4 ignition-density maps and 8 weather types.

Length of Fire Season

The length of the fire season was approximated using a drought index. I modeled the soil moisture regime using the soil–water submodel of the FACET model (Urban et al. 2000) and used the resulting estimate of the annual number of drought-days to approximate the length of the fire season across the study area. Inputs to the soil–water submodel include monthly minimum and maximum temperature and precipitation, elevation, slope, aspect, soil depth, soil texture, and leaf area index of the site. The soil–water submodel simulates soil moisture as the balance of water demand (energy supply) and water supply. Water demand is based on temperature and radiation, and so varies with elevation and topographic position. Water supply depends on water inputs (precipitation and snowmelt) and water storage in the soil. As output, the model tallies a drought-day index to determine the number of days during the growing season that the soil water is at or below wilting point. Temperature and

Table 3. Weibull distribution parameters by elevation.

Elevation (m)	σ	η
500	145.3	3.777
600	140.2	3.380
700	132.8	3.258
800	125.5	3.089
900	117.0	2.824
1000	109.7	2.755
1100	102.0	2.416
1200	95.4	1.831
1300	86.9	1.591
1400	76.9	1.274
1500	67.3	1.013
1600	58.5	0.843
1700	47.9	0.762
1800	37.4	0.815
1900	30.9	0.741
2000	25.9	0.787
2100	20.7	0.843
2200	15.0	0.789
2300	11.6	0.847
2400	9.1	0.806
2500	8.8	0.892
2600	6.8	0.881

precipitation data were obtained from nearby weather stations, and then lapse rates of these were regressed on elevation.

I ran the soil–water submodel to generate 100 years of the drought-day index for 26 elevations from 500 m to 3000 m at 100-m intervals, all flat ground, and all with the same soil depth, soil type, and leaf area on the site. As such, the variability of the drought-day index across the simulated elevation gradient is due to the differences in temperature and precipitation across this gradient.

The 100 years of drought-day index were put in rank order for each elevation, transformed following Latham and Rothermel (1993), and non-linear regression was used to estimate the parameters of the Weibull distribution from the least squares coefficients of a line fit to the transformed data. The values obtained for σ and η from the drought-day index ranks for each elevation interval are listed in Table 3.

Weighted Average Probability

Equation 2 and the values computed for w, σ, and η were used to compute the probability of burning for each 120-m grid cell on the landscape. Probability of burning was computed for each of the 32 cumulative spread-time maps. These were combined using a weighted average approach where the weights used are according to frequencies of occurrence (Table 2).

RESULTS

The weighted average annual probability of burning estimated by the model is shown in Figure 2 for the Selway-Bitterroot Wilderness. The mean value across the entire landscape was 0.019 with a standard deviation of 0.023. The maximum annual probability for a 120-m grid cell was 0.215. The highest probabilities (Figure 2) surrounded the highest ignition densities (Figure 1), which occurred along the east face of the Bitterroot front and in the canyon bottoms in the interior of the Selway-Bitterroot Wilderness.

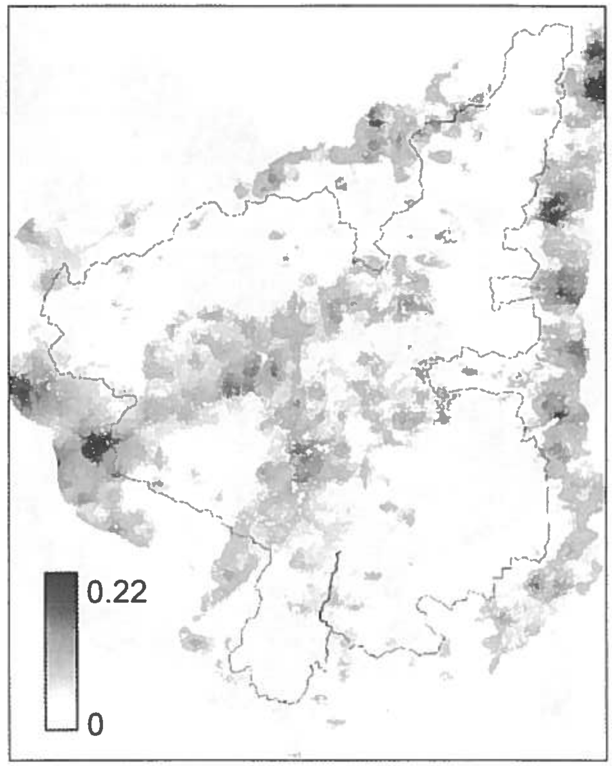

Fig. 2. Annual probability of burning predicted by mechanistic modeling approach in the Selway-Bitterroot Wilderness, Idaho and Montana.

The predicted probabilities were converted to the expected number of times burned in 115 years (Figure 3) for comparison with observed fire occurrence patterns during 1880–1994 (Figure 4). The model overpredicted the number of times burned and the amount of area reburned. The average number of times burned was predicted to be 2.3, whereas the average for the observed record was only 0.6. The proportion of the total area burning two or more times was predicted to be 0.66, and the proportion burning two or more times during 1880–1994 was only 0.12. The highest fire frequencies were predicted in the canyon bottoms in the interior of the wilderness, as well as along the east face of the Bitterroot Mountains. The observed record showed highest frequencies in the interior of the wilderness, but low frequencies along the east face of the Bitterroot Mountains.

DISCUSSION

For any patch of ground to burn, two requirements must be met: the fuels must be burnable, and there must be an ignition source. The patch of ground may burn because it is ignited from a human-caused spark or a lightning strike, but more likely, the ignition source is a fire that starts in another location and spreads across a landscape to reach the patch of ground. The spatial context of fire spread and the spa-

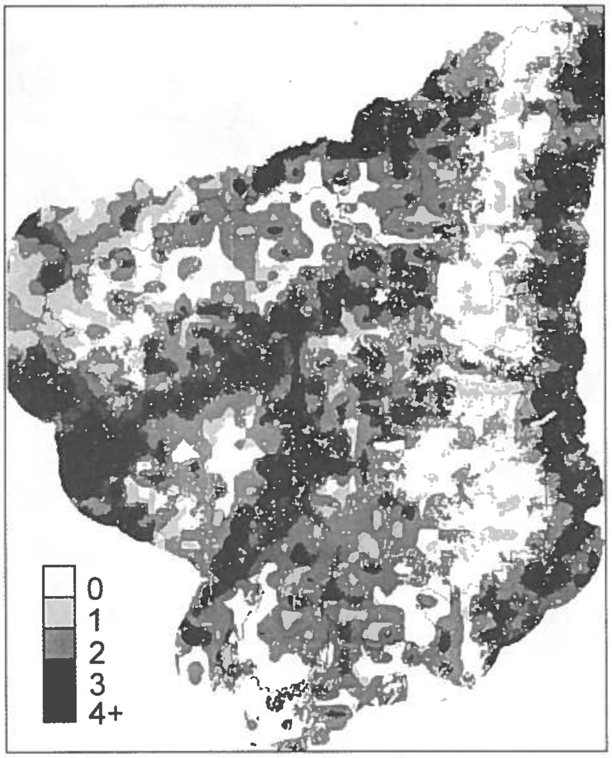

Fig. 3. Predicted number of times burned in 115 years in the Selway-Bitterroot Wilderness, Idaho and Montana.

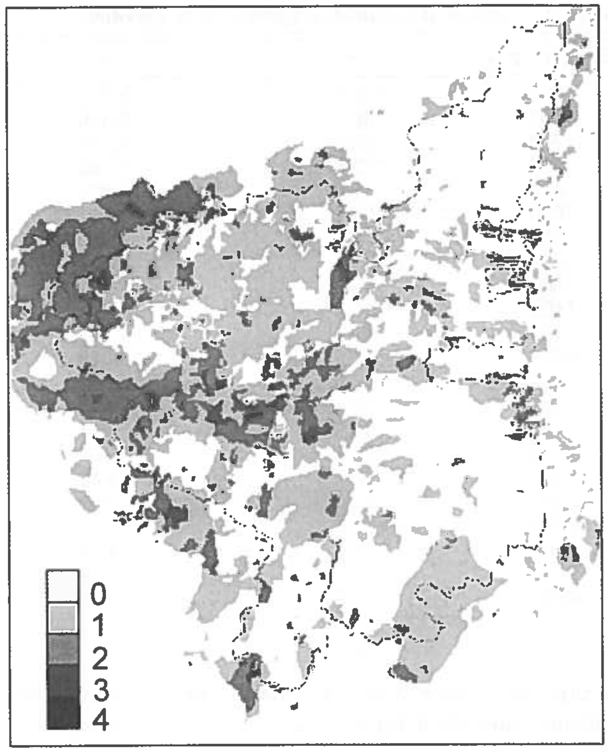

Fig. 4. Observed number of times burned in 115 years (1880–1994) in the Selway-Bitterroot Wilderness, Idaho and Montana.

tial configuration of burnable fuels and ignitions are therefore critical for predicting the probability of burning (Chou et al. 1990). Unfortunately, most statistical models have not considered these important spatial factors.

A mechanistically based modeling approach, such as the one presented here, can explicitly account for and address the spatial context of fire spread and fuels. The influence of the spatial arrangement of ignitions, topography, and fuels can be seen in the clumpy nature of the probability surfaces generated, where high probabilities are aggregated around the areas where ignitions are most dense (Figure 2).

Statistical approaches are also limited by available data. The use of historical fire data to develop statistical models is feasible only in areas where these data exist. Although one might expect that sufficient data are available in areas that have experienced very frequent fire regimes, in reality, even many of these areas lack the number of recorded observations needed to develop strong predictive models. Furthermore, today's fire management challenges extend far beyond those areas with high-frequency fire regimes.

The methods described and used here do not require information on historical fire perimeters, but instead rely upon a mechanistic approach to generate probability surfaces. As such, this approach is especially suited for areas that lack empirical fire history data, either because of inadequate data collection or lack of fire activity. Even in areas with extensive fire history data, such as the Selway-Bitterroot Wilderness, the approach described here should yield better results than statistical analyses. For example, logistic regression of the 115 years of fire perimeter data for the Selway-Bitterroot Wilderness is highly dominated by elevation, and produces probabilities that essentially track elevation (Rollins 2000). The modeling approach described here produces probability patterns that are spatially aggregated, due to the influence of ignition locations and the spatial context of burnable fuels surrounding ignition locations. Although the model overpredicted the probability of burning, the results were encouraging because no attempt was made to calibrate the results to the observed 20th-century patterns. For example, the drought-day distribution used to derive the Weibull parameters may not be the best estimate of the length of the fire season, and adjustments to these parameters may be needed, improving the correspondence of the results to the 20th-century data.

The predicted probabilities may be higher than the 20th-century fire history record in part because of the success of fire suppression efforts; the effects of fire suppression need to be reconciled with the predicted fire occurrence patterns. The largest discrepancy between predicted and observed patterns occurred east of the Bitterroot front, which is also where most suppression efforts are focused (Law et al. 1997). Additional analysis of the 20th-century fire data is required to discern the possible influence of management actions on observed occurrence patterns.

The model presented here accounts for the spatial context of ignitions and fuels, and, as such, the results are sensitive to ignition locations. Historical ignition patterns were used, with the assumption that these are reliable estimates of future ignition patterns. However, anthropogenic-ignition locations could change over time due to changes in development patterns and recreation use, and spatial patterns in natural ignitions might vary with long-term weather and climate changes, as well as changes in vegetation cover. A sensitivity analysis exploring the effect of alternative ignition-density patterns on the probabilities of burning will be conducted in the next phase of model development.

A more critical point, however, is that ignition patterns may vary in time as well as in space. Early-season ignition patterns have not been distinguished from late-season patterns, and therefore the model assumes that all ignitions have the entire length of the fire season to burn. In reality, certain areas may not experience ignitions until late in the fire season, thereby having less time to spread across the landscape. The model will be improved to account for this situation, reducing probability values, especially in areas with primarily late-season ignitions.

An uncertainty in any fire history analysis is the condition of the vegetation and fuels during the time of the record. The probabilities computed by the model presented here are based on estimates of current fuels, whereas the fire patterns during 1880–1994 are the result of fire burning through fuels that changed through time due to vegetation dynamics. If the basic methods presented here were coupled to a simulation model of vegetation dynamics, the annual probability of burning could reflect the changes in fuels through time. In turn, the probability of burning could be used by the vegetation dynamics model to simulate fire regimes. The integration of these methods with a landscape succession model is currently being planned.

MANAGEMENT IMPLICATIONS

Today's fire management challenges require that managers strategically allocate and plan their activities across entire landscapes. Information on probability of burning is extremely valuable to managers who are striving to prioritize fuels treatments across a landscape. Furthermore, estimates of probability of burning can be combined with spatial information on the social and ecological values that may be affected by fire and then used in designing strategic fire and fuels management plans (Miller et al. 2000).

To develop strategies for the restoration of wildland fire and fire-prone ecosystems, knowledge of the natural fire regime is essential. Managers often do not have this information because of successful fire suppression efforts and a lack of comprehensive fire histories. In the absence of fire history information, estimates of the probability of burning might be used to derive potential natural fire regimes and preliminary targets for restoration objectives.

The approach described in this paper requires only a basic set of data: a digital elevation model, a fuels map, climatic data, and historical ignition locations. The major advantage of this approach is its applicability to any landscape where these data exist. Although this approach provides useful information for long-term fire and fuels management planning, it is not suitable for incident management.

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