Mapping Probability of Fire Occurrence in San Jacinto Mountains, California, USA

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ABSTRACT / An ecological data base for the San Jacinto Mountains, California, USA, was used to construct a probability model of wildland fire occurrence. The model incorporates both environmental and human factors, including vegetation, temperature, precipitation, human structures, and transportation. Spatial autocorrelation was examined for both fire activity and vegetation to determine the specification of neighborhood effects in the model. Parameters were estimated using stepwise logistic regressions. Among the explanatory variables, the variable that represents the neighborhood effects of spatial processes is shown to be of great importance in the distribution of wildland fires. An important implication of this result is that the management of wildland fires must take into consideration neighborhood effects in addition to environmental and human factors. The distribution of fire occurrence probability is more accurately mapped when the model incorporates the spatial term of neighborhood effects. The map of fire occurrence probability is useful for designing large-scale management strategies of wildfire prevention.

On the average, some 250,000 wildland fires occur in the United States each year on federal, state, and private lands. Most of these fires are quickly controlled by the planned local protection forces at relatively small size. However, a significant number exceed the ability of the initial attack forces to contain them and escape to cause substantial damage to natural resources and property and loss of life. In order to minimize this threat of loss from wildfires, fire managers must be able to plan protection strategies that are appropriate for individual local areas (Chou 1991a). A prerequisite for this planning is the ability to assess and map for broad areas the local potential for a major fire to occur (Chou 1991b). Based on such geographic information, managers can establish priorities over the area for prevention activities to reduce the risk of wildfire ignition and spread, as well as for the allocation of suppression forces to improve the probability for initial attack to control fires that do occur in areas of high concern.

In this article, fire occurrence probability is defined as the probability for major fires to occur in an area. Mapping fire occurrence probability requires sophisticated spatial analyses because major wildland fires result from complicated spatial processes that are driven by various factors, such as vegetation, topography, and weather. Human factors such as forest management activities, prevention measures, fuel treatment, residential patterns, and recreational activity also affect the potential for major wildland fires. The distribution of wildland fires is further affected by neighborhood effects, i.e., each area affects, and is affected by, its surrounding areas (Chou and others 1990). For instance, two areas of identical environmental and human conditions may be of different degrees of fire occurrence probability if one is surrounded by high-density chaparral and the other is surrounded by bare ground and lakes.

In order to map fire occurrence probability, it is necessary to construct a probability model of fire occurrence based on variables that are significant to fires. Such a complicated task can be accomplished effectively using the modern technology of geographic information systems (GIS) (Lowell and Astroth 1989, Chou 1992a). In general, a GIS is an organized system of computer hardware, software, and geographic information, designed specifically for organizing and analyzing the complex spatial relationships among multiple components of significance (Environmental Systems Research Institute 1987).

As environmental conditions vary from time to time, maps of fire occurrence probability may not remain useful for a long period of time. For instance,

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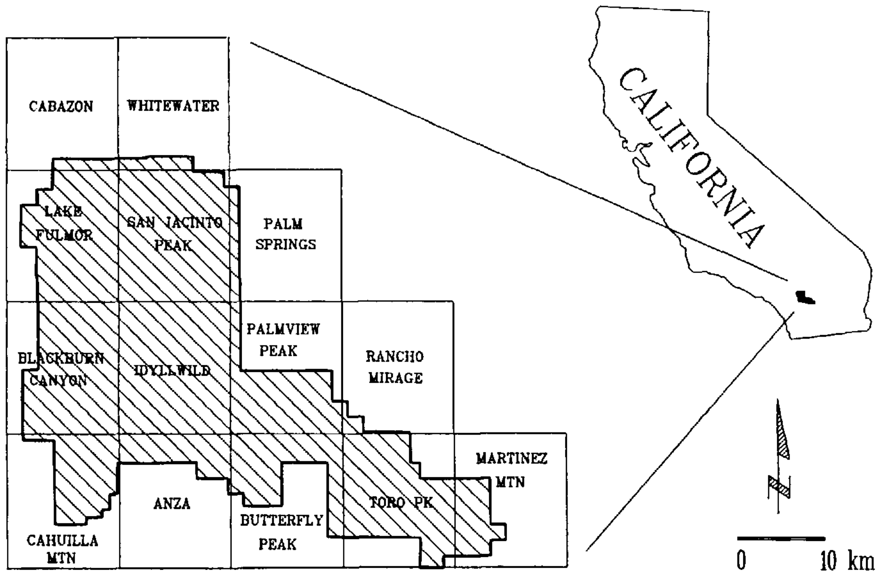

Figure 1. The San Jacinto Ranger District, San Bernardino National Forest, California (7.5-minute quadrangles).

the fire occurrence probability of an area drops to zero immediately after a burn and adjacent areas enjoy a decrease in fire potential due to neighborhood effects. Fire occurrence probability also changes periodically in response to variations in local weather conditions or seasonal events. The ideal model of fire occurrence probability must be flexible enough for frequent updating of current conditions. Frequent updating of fire potential requires a well-designed data base and a GIS.

Since 1985 we have used a GIS to construct a data base with multiple variables related to wildland fires in the San Jacinto Mountains in southern California. In this study, we used this data base to test different models for the explanation and prediction of wildland fires. The distribution of fire occurrence probability was mapped based on the estimated parameters of the best-fit model.

Study Area and Geographic Units

The study area is the San Jacinto Ranger District of the San Bernardino National Forest, 150 km east of Los Angeles, California. The data base is organized into 14 USGS 15-min quadrangles (Figure 1). The well-recorded history of fire activity provides the data necessary for testing probability models of fire occurrence (Figure 2). In the fire activity coverage, the areal extent of major fires that occurred between 1911 and 1984 (file data, San Bernardino National Forest) are digitized into polygons, coded with years of burns.

The diversity in environmental and human conditions makes this area an ideal area for wildland fire management. Vegetation is dominated by highly flammable chaparral, especially on steep terrain. Less flammable open stands of desert chaparral cover the arid eastern margin of the study area. Conifer forests cover highest elevations and basin floors. Land ownerships include national forests, large private holdings, and Indian reservations.

The first step for building a model of fire occurrence is to define geographic units according to explicitly specified criteria. Two criteria are considered in this study. First, geographic units must represent areas of homogeneous surface in terms of a characteristic that is meaningful to wildland fires. Second, there must be a sufficient number of geographic units for valid statistical testing. With these concerns, the vegetation coverage is most appropriate, among the existing data layers, for defining geographic units. Each polygon delineated in the vegetation coverage represents an area of relatively homogeneous vegetation type.

Vegetation was mapped, using standard aerial-photo interpretation procedures (Minnich 1987), from 1:20,000-scale color aerial photographs provided by the San Bernardino National Forest. The original vegetation coverage is organized into three data layers that are not mutually exclusive—shrubs, oaks, and conifer forests—coded into 24 species listed in Table 1. Delimitation of vegetation polygons within each layer was based on species dominance. Figure 3 shows the composite vegetation coverage that was

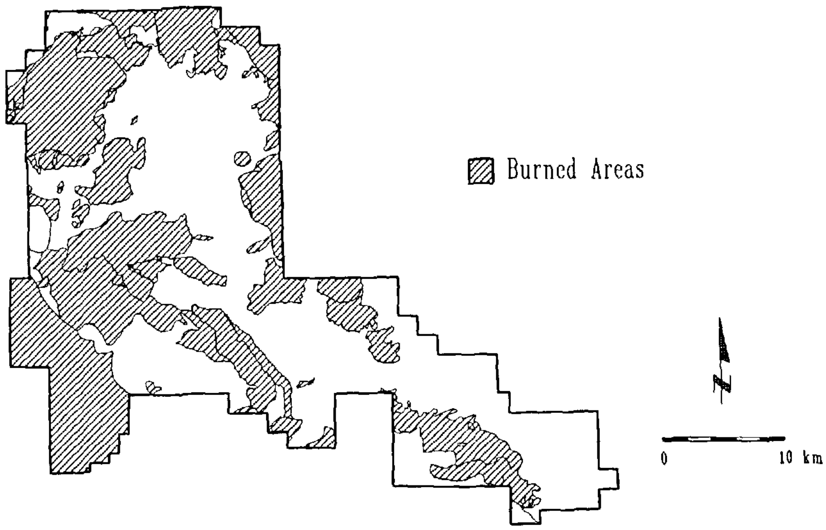

Figure 2. Fire activity between 1911 and 1984. Shaded polygons show areas that were burned at least once during this period.

Table 1. The vegetation classes

Group	Dominating species
Conifers	
BD	*Pseudotsuga macrocarpa*
CJ	Mixed conifer forest/*Pinus jeffreyi*
CP	*Pinus coulteri*
JP	*Pinus jeffreyi*
LL	*Pinus contorta/Pinus flexilis*
PM	*Pinus monophylla*
PP	Mixed conifer forest/*P. ponderosa*
PQ	*Pinus quadrifolia*
WS	*Abies concolor/Pinus lambertiana*
Oaks	
QA	*Quercus agrifolia*
QC	*Quercus chrysolepis*
QK	*Quercus kelloggii*
Shrubs	
AG	Agriculture
BA	Barren
BC	Chaparral/bedrock
CH	Chamise chaparral
CS	Coastal sage scrub
DE	Desert scrub
DC	Desert chaparral
GB	Great Basin sage scrub
MC	Mixed chaparral
ME	Meadow
RS	Red shank chaparral
TC	Timberland chaparral

generated by overlaying the three layers and reclassifying the 24 species into eight major categories adapted to National Fire Danger Rating fuel models (Deeming and others 1977), i.e., six vegetation types plus water and bare ground. The composite vegetation coverage is henceforth referred to as the base coverage, and the 803 polygons delineated in the base coverage define the geographic units for analysis throughout this study.

Extracting Data for Analysis

As explained below, environmental factors extracted from the data base and processed for analysis include temperature, precipitation, and the expected period of fire rotation due to vegetation type.

Temperature data were obtained from mountain station reports of July maximum temperatures (selected to represent conditions when fires are most likely to be active) and interpolated by altitude based upon mean radiosonde profiles taken by the National Weather Service Station at San Diego (Chou and others 1990). All stations, regardless of terrain, were near 3°C above ambient temperatures controlled for altitude due to superheating. The coverage of July maximum temperature was created by assigning mean sounding temperature to altitude contours plus 3°C (Figure 4). To obtain the data of the temperature variable, TEMP, we first constructed a composite coverage by overlaying the base coverage and the coverage of July maximum temperature. Then, from the composite coverage, we calculated the mean temperature of each geographic unit by averaging with areal adjustment the values of different temperature zones within the geographic unit.

The coverage of annual precipitation is constructed by contouring the reported data of existing weather stations (Figure 5). For large areas without stations, precipitation is interpolated from terrain based on the available data of existing weather stations. The interpolation assumes that precipitation increases with elevation on windward slopes and de-

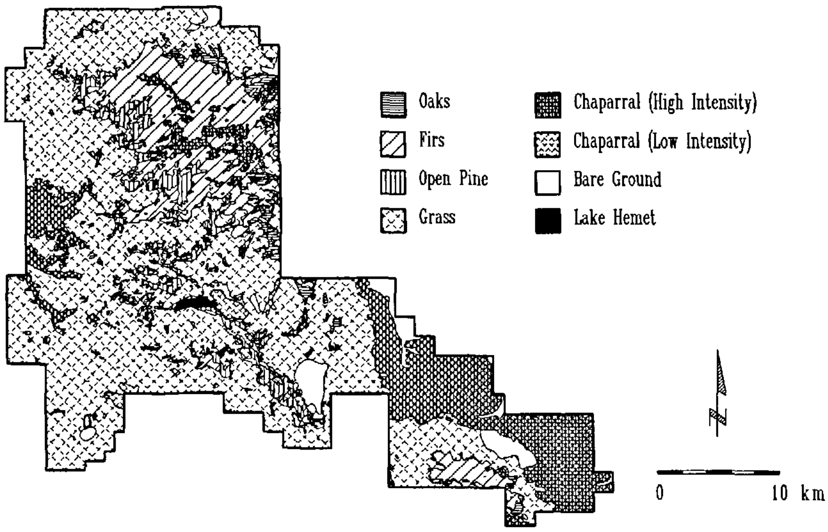

Figure 3. The composite coverage of vegetation.

Figure 4. Isotherms of July maximum temperature (isotherms in degrees Centigrade).

creases on leeward slopes due to rain shadows and that winds aloft are largely from the southwest and west-southwest (250–220 degrees) during winter cyclonic storms that provide the major sources of precipitation in the study area (Minnich 1984). This line coverage is converted into a polygon coverage and then overlain onto the base coverage to generate a composite coverage of vegetation and precipitation. From the composite coverage, the variable of precipitation, RAIN, is obtained by averaging with areal adjustment the values of different precipitation levels within each geographic unit.

Fire rotation period is defined as the mean time between burns, i.e., the time needed to burn an area equivalent to the vegetation area (Pickett and White 1985). Based on the assumption that fuel types are closely related to burn propensity, the general vegetation categories are translated into fire rotation period weights listed in Table 2. The fire rotation weights were defined according to estimated rotation period based on fire return periods of chaparral vegetation in San Diego County and adjacent northern Baja California, Mexico (Minnich 1989, Minnich and Dezzani 1991). A larger rotation weight, ROTA, is associated with a higher degree of burn propensity.

Three human factors were extracted for analysis: structures, roads, and trails. Human structures were digitized from the USGS 7.5-min topographic maps edited in1981. Each dot in Figure 6 denotes the location of a building, a campground, or a lookout tower. Using a GIS function for identifying nearest features and calculating the shortest distance, the variable

Figure 5. Isohyets (in centimeters) of annual precipitation.

Table 2. Vegetation and fire rotation weight

Code	Vegetation	Rotation period	Rotation
1	Oaks	50 years	1.0
2	Firs	50 years	1.0
3	Open pine	50 years	1.0
4	Grass	100 years	0.5
5	Chaparral (H)	50 years	1.0
6	Chaparral (L)	200 years	0.25
7	Bare ground	Infinity	0.0
8	Water	Infinity	0.0

BUILD, the nearest distance from each geographic unit (defined from the base coverage) to a building, is obtained. Likewise, the variable CAMP, which denotes the nearest distance from each geographic unit to its nearest campground, is derived.

Roads and trails were also digitized from the topographic map (Figures 7 and 8). For each geographic unit, the nearest road or highway is identified by relating the coverage of roads and that of trails to the base map. A variable, ROAD, is then defined by calculating the Euclidean distance between the geographic unit and its nearest road or trail.

Modeling Fire Occurrence Probability

In building the model of fire occurrence probability, the approach adopted in this study is one of minimum complexity. The model structure is made as simple as possible without losing forecasting accuracy. Since model building involves sophisticated analytical procedures, the main concern is to avoid building a model too complicated for practical applications. We started with a basic model, which contains only the minimum environmental and human factors. Spatial factors were added only if the basic model failed to generate satisfactory results.

The Basic Model of Fire Occurrence Probability

The logistic model is suitable for modeling the probability of fire occurrence (Donoghue and Main 1985, Martell and others 1987, Chou 1990). Formally, the logistic model of fire occurrence probability can be specified as:

$$P_i = \frac{EXP\,(U_i)}{1 + EXP\,(U_i)}$$

where P_i denotes the probability for a fire to occur in the ith geographic unit.

This model ensures that the probability of fire occurrence in each geographic unit, determined by the quantity U, has a value between zero and one. A larger U denotes a greater propensity to burn and is associated with a higher degree of fire potential. According to the logistic function, when U approaches the positive infinity, the probability approaches one and implies a definite burn in the next period. As U approaches the negative infinity, the probability drops to zero, indicating that the geographic unit will not burn.

The probability of fire occurrence is not equivalent to probability of ignition because not all ignitions develop into major fires. Some fires may be put out quickly by effective suppression action, while others may burn out on their own due to lack of fuel. It follows that for an ignition to develop into a major

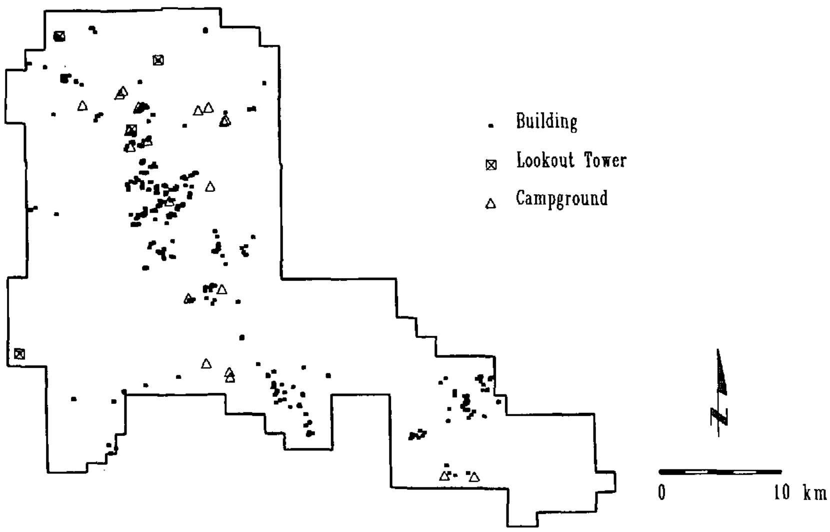

Figure 6. Buildings and campgrounds were digitized from the USGS topographic maps.

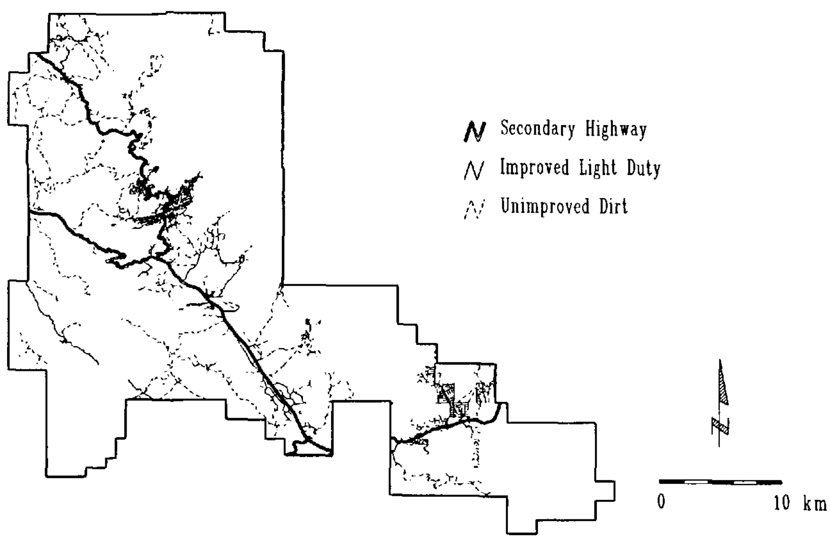

Figure 7. Roads were digitized from the USGS topographic maps.

fire, the human and environmental factors must favor the spread of the fire or at least not suppress it.

The quantity of U is specified by the explanatory variables that represent environmental and human factors meaningful to fire occurrence. Based on data extracted from the San Jacinto data base, a basic model of fire occurrence was specified as:

$$\begin{aligned} U_i = {} & \beta_0 \\ & + \beta_1 \mathrm{AREA}_i + \beta_2 \mathrm{PERI}_i + \beta_3 \mathrm{BLDG}_i \\ & + \beta_4 \mathrm{ROTA}_i + \beta_5 \mathrm{CAMP}_i + \beta_6 \mathrm{ROAD}_i \\ & + \beta_7 \mathrm{TEMP}_i + \beta_8 \mathrm{RAIN}_i + e \end{aligned}$$

where AREA_i is the area of the ith geographic unit; PERI_i denotes the perimeter of the geographic unit; BLDG_i measures the distance between the centroid location of the ith geographic unit and its nearest building; ROTA_i is the variable of expected rotation period determined by vegetation; CAMP_i is the distance between the geographic unit and the nearest campground; ROAD_i represents the distance between the geographic unit and the nearest road; TEMP_i denotes the average July maximum temperature in the geographic unit; RAIN_i is the average annual precipitation in the geographic unit; e is a random error term; β_j is the parameter for the jth variable in consideration.

Coefficients of the parameters were estimated using the stepwise logistic regression (LR) program of BMDP (University of California, Los Angeles 1987). A chi-square (χ^2) test was used to identify the variables that are statistically significant to the explanation of wildland fire occurrence. The final structure of the

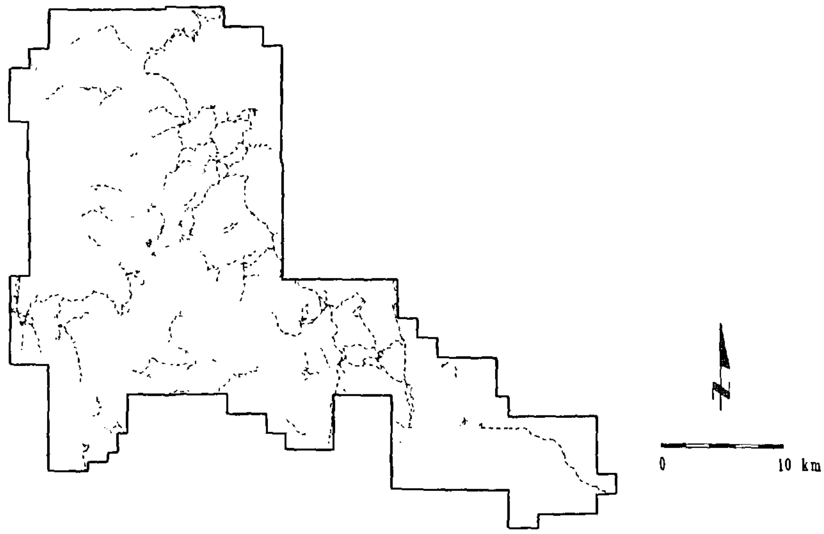

Figure 8. Trails were digitized from the USGS topographic maps.

Table 3. Basic model of fire occurrence

Log likelihood = −473.001

Goodness of fit chi-sq (2*O*LN(O/E)) = 946.002
D.F. = 794
P value = 0.000

Goodness of fit chi-sq (Hosmer-Lemeshow) = 9.026
D.F. = 8
P value = 0.340

Goodness of fit chi-sq (C. C. Brown) = 2.672
D.F. = 2
P value = 0.263

Maximum PCE = 68.12

Term	Coefficient	SE	Coef/SE
AREA	0.2327E-07	0.145E-97	1.60
PERI	0.1232E-03	0.341E-04	3.62
BLDG	0.3288E-04	0.547E-04	0.602
ROTA	−0.2160E-02	0.491E-03	−4.40
CAMP	−0.1995E-04	0.218E-04	−0.916
ROAD	−0.9282E-03	0.559E-03	−1.66
TEMP	0.3070	0.424E-01	7.23
RAIN	−0.7312E-02	0.881E-02	−0.830
CONSTANT	−7.778	1.50	−5.20

probability model incorporates only the explanatory variables that are statistically significant.

The results of the basic model are listed in Table 3. In the stepwise logistic regression, the criterion for a variable to enter the model was intentionally set loose in order to obtain the estimated parameters of all variables for further comparisons, regardless of each variable's significance level. Temperature (TEMP), the variable of fire rotation period (ROTA), and perimeter (PERI) are significant in explaining the distribution of wildland fires. The maximum percentage correct estimation (PCE) of this model is 68.12. However, all the χ^2 statistics indicate that the model is not satisfactory and modifications are needed.

Figure 9 shows the distribution of fire occurrence probability based on the basic model. Only the variables that are statistically significant were employed. Geographic units are classified into thee levels of fire potential: less than 50%, between 50% and 80%, and greater than 80%. The map shows that the spatial distribution of fire occurrence probability, as described by the basic model, is dominated by large parcels of great fire potential. The spatial pattern, apparently biased toward greater values of fire occurrence probability, is consistent with the statistics in suggesting the need of modifications on model specification. To refine the model, neighborhood effects must be incorporated.

Measuring Neighborhood Effects by Spatial Autocorrelation

Neighborhood effects can be evaluated by statistics of spatial autocorrelation. Spatial autocorrelation measures the degree to which the distribution of a spatial phenomenon is correlated with itself. A positive spatial autocorrelation exists if the occurrence of one event of the spatial phenomenon under consideration tends to attract similar events to take place in its neighborhood, which usually results in a clustered pattern of distribution. If the occurrence of one event of the spatial phenomenon tends to prevent similar events from occurring in the immediate neighborhood, which results in a scattered or uniform pattern of distribution, then the phenomenon displays a neg-

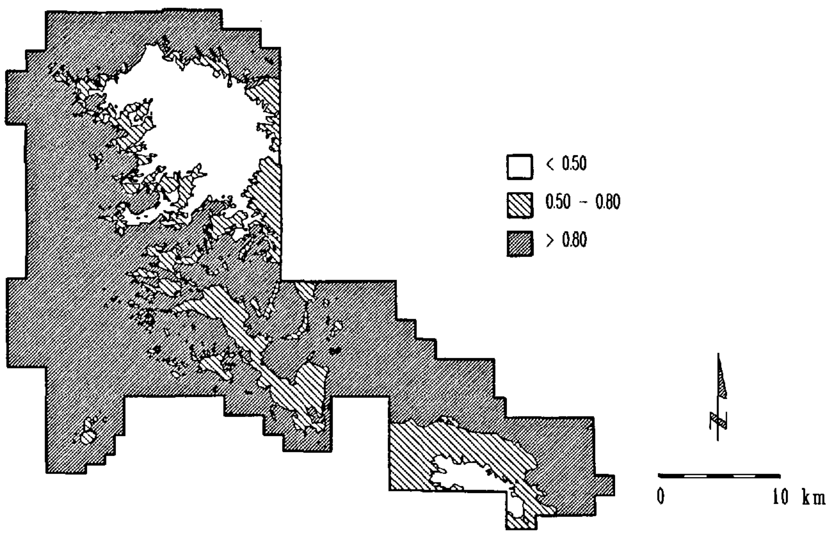

Figure 9. Probability of fire occurrence estimated from the basic model.

ative spatial autocorrelation. It is also possible that neither of the extreme types dominates the distribution, which results in a relatively random pattern of distribution. In this case, the spatial autocorrelation is insignificant.

Moran's I coefficient (Moran 1948), the earliest developed statistic for spatial autocorrelation, is adopted for evaluating neighborhood effects. The I coefficient is a function of spatial autocovariance standardized by variance and spatial arrangement, such that

$$I = \frac{N}{\Sigma\Sigma W_{ij}} \frac{\Sigma\Sigma\, W_{ij}(X_i - X)(X_j - \bar{x})}{\Sigma(X_i - \bar{x})^2}$$

where N is the number of geographic units; X_i is the observed value of variable X for the ith unit; W_{ij} is a zero–one weighting function of contiguity which equals one if the ith unit and the jth unit share a common boundary, and equals zero otherwise. According to Cliff and Ord (1981), the expected value of Moran's I under the assumption that the random variable X is normally distributed is

$$E(I) = 1/(1 - N)$$

The expected value is always negative and approximates zero as the number of polygons approaches infinity. The variance is

$$\mathrm{VAR(I)} = \frac{N^2S_1 - NS_2 + 3(\Sigma\Sigma\, W_{ij})^2}{(\Sigma\Sigma W_{ij})^2(N^2 - 1)}$$

where

$$S_1 = (1/2)\Sigma\Sigma(W_{ij} + W_{ji})^2 \text{ and } S_2 = \Sigma(\Sigma W_{ij} + \Sigma W_{ji})^2$$

Table 4. Spatial autocorrelation of fire activity

Variable	Moran's I	Z value
Binary	0.203	8.441
Areal-adjusted	0.380	15.806

The standard normal deviate, Z, based on the mean and variance of Moran's I, is suitable for testing the significance of spatial autocorrelation, such that

$$Z = [I - E(I)]/d_I$$

where d_I denotes the standard deviation of I.

Spatial autocorrelation was evaluated for the distribution of both previous fire activity and vegetation. The rationale is that a significant level of spatial autocorrelation of fire activity illustrates neighborhood effects in the distribution of wildland fires. The spatial autocorrelation in the distribution of vegetation must also be evaluated because it is assumed that the kind of vegetation determines fuel buildup rates.

The spatial autocorrelation of fire activity is evaluated by measuring the record of fire at two different scales, the nominal scale where a binary code of burned or not is applied to each unit, and a ratio scale where the percentage of burned area in each unit is calculated. Table 4 indicates that fire activity is positively spatially autocorrelated, i.e., past five activity in adjacent areas tends to increase the probability of fire occurrence in geographic area being mapped. Furthermore the autocorrelation is more evident when fire activity is measured in the ratio scale, which is consistent with the finding of a previous study on the relationships between spatial autocorrelation and map resolution (Chou 1991c). An important implica-

Table 5. Spatial autocorrelation of vegetation

Vegetation type	Moran's I	Z value
Conifer	0.067	4.795
BD	0.127	9.207
CJ	0.077	5.537
CP	0.036	2.630
JP	0.329	23.678
LL	0.328	23.937
PM	0.116	8.373
PP	0.467	33.699
PQ	0.075	5.412
WS	0.291	20.964
Oak	0.278	19.971
QA	0.109	7.883
QC	0.287	20.635
QK	0.356	25.609
Shrub	0.361	25.900
AG	0.000	0.149
BA	0.058	4.191
BC	0.528	38.332
CH	0.284	20.441
CS	0.000	0.061
DE	0.194	17.020
DC	0.249	17.956
GB	0.179	13.045
MC	0.493	35.387
ME	0.186	13.425
RS	0.288	20.683
TC	0.526	37.863

tion of the results is that a spatial term to represent neighborhood effects is needed in the construction of fire occurrence models.

Spatial autocorrelation was also evaluated for vegetation. Table 5 lists the results for 24 vegetation classes. All three general classes illustrate a positive spatial autocorrelation which is statistically significant. Furthermore, shrub classes have the highest level of spatial autocorrelation, i.e., shrubs tend to form clusters thereby increasing the degree of fire potential. The results clearly suggest the need of incorporating a spatial term of neighborhood effects in the model of fire occurrence probability.

Modeling Fire Occurrence with Neighborhood Effects

To incorporate neighborhood effects in the fire occurrence model, we define a term *NBR* as the ratio of the number of burned adjacent units to the total number of adjacent units. Adding this term, the modified model becomes:

$$U_i = \beta_0 + \beta_1 \mathrm{AREA}_i + \beta_2 \mathrm{PERI}_i + \beta_3 \mathrm{BLDG}_i + \beta_4 \mathrm{ROTA}_i + \beta_5 \mathrm{CAMP}_i + \beta_6 \mathrm{ROAD}_i + \beta_7 \mathrm{TEMP}_i + \beta_8 \mathrm{RAIN}_i + \beta_9 \mathrm{NBR}_i + e$$

Table 6. Modified model of fire occurrence

Log likelihood = −390.090

Goodness of fit chi-sq (2*O*LN(O/E)) = 780.181
D.F. = 793
P value = 0.621

Goodness of fit chi-sq (Hosmer-Lemeshow) = 14.661
D.F. = 8
P value = 0.066

Goodness of fit chi-sq (C. C. BROWN) = 26.739
D.F. = 2
P value = 0.000

Maximum PCE = 78.58

Term	Coefficient	SE	Coef/SE
AREA	0.5682E-07	0.155E-07	3.65
PERI	0.3037E-03	0.491E-04	6.18
BLDG	0.8500E-04	0.609E-04	1.40
ROTA	−0.3039E-02	0.566E-03	−5.37
CAMP	−0.8642E-05	0.244E-04	−0.355
ROAD	−0.5499E-03	0.632E-03	−0.871
TEMP	0.2859	0.463E-01	6.18
RAIN	−0.1988E-01	0.100E-01	−1.98
NBR	5.902	0.616	9.58
CONSTANT	−12.40	1.75	−7.11

where notations are identical to those in the basic model. The estimated coefficients and statistics of the modified model are listed in Table 6. The PCE increases to a much higher level of 78.58, compared to that of the basic model. All the χ^2 statistics are statistically significant, suggesting that the model is satisfactory for explaining the distribution of wildland fires.

The comparison between the log likelihood of this table and that of Table 3 indicates that the improvement over the basic model, due to the inclusion of NBR, is statistically significant. Furthermore, the high significance of the spatial term suggests that neighborhood effects play an important role in the distribution of wildland fires. This finding has two important implications for wildfire management. First, the explanation and prediction of fire occurrence must take into consideration the neighborhood effects of spatial processes. As such, models of fire occurrence probability must incorporate, in addition to environmental and human factors, a spatial term that represents neighborhood effects. Second, effective spatial strategies of wildfire management can be developed by utilizing the advantages of neighborhood effects. For instance, a planned burn applied to a location of maximum neighborhood effects can be much more effective than that applied to another location (Chou 1992b).

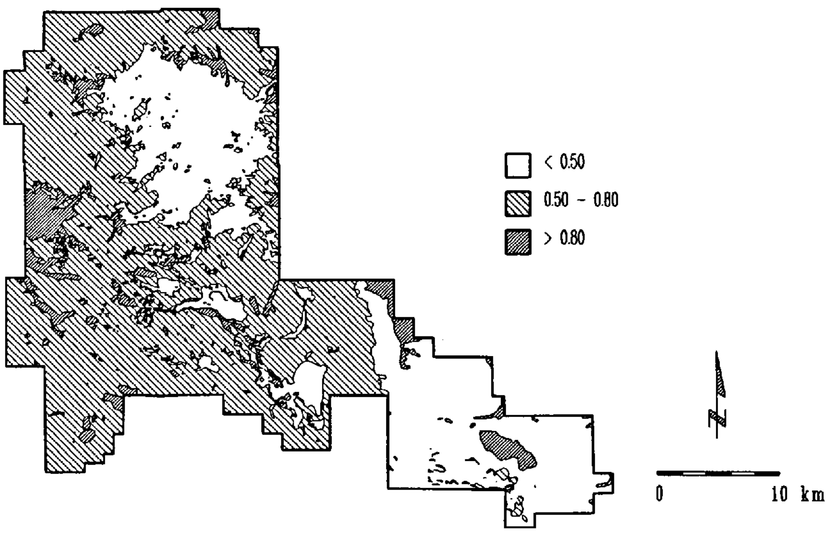

Figure 10. Probability of fire occurrence estimated form the modified model.

In this modified model, the variables that are statistically significant include the spatial term of neighborhood effects (NBR), fire rotation weight (ROTA), temperature (TEMP), perimeter (PERI), and area (AREA). Among them, perimeter and areas are adjusting factors to take into account the varying size of geographic units. If geographic units are divided into smaller units of similar size, these two variables may become unnecessary.

Again, only these significant variables were employed in constructing the spatial distribution of fire occurrence probability based on the modified model (Figure 10). The pattern apparently removed the spatial bias due to large parcels of great fire potential depicted in Figure 9. The differences in the spatial pattern of fire occurrence probability between these models have important implications. First, since neighborhood effects play an important role in the distribution of wildland fires, the explanation and prediction of fire potential must take into consideration the effects of such spatial processes. The distribution of fire occurrence probability can be more accurately mapped when the model incorporates, in addition to environmental and human-related factors, a spatial term of neighborhood effects. Maps of fire occurrence probability are especially useful for identifying critical zones of fire potential and assigning priority to areas of special concern. Second, the design of effective management strategies of fire prevention must consider neighborhood effects of each preventive measure. Comparisons between Figure 9 and Figure 10 suggest that the probability of fire occurrence for large parcels of great fire potential can be reduced by carefully implementing a preventive treatment which generates wide spread neighborhood effects. Operational methods for evaluating different strategies of wildfire prevention based on neighborhood effects are available (Chou 1992b).

Conclusion

In a previous study based on the data for the Idyllwild Quadrangle, Chou and others (1990) compared different spatial weighting functions in order to construct a model of large fire occurrence probability. This study includes the entire San Jacinto Ranger District and deals with a data base much larger than for the Idyllwild quadrangle. In this analysis we show that the model building and spatial analyses can be applied to a district of practical significance and the results can be empirically useful for wildland fire management. The methodology developed in this study is especially useful for empirical applications in three areas.

First, areas of great fire potential can be outlined from the map of fire occurrence probability. Figure 10 shows parcels of great fire potential where the fire occurrence probability is greater than eighty percent. For fire managers at the San Jacinto Ranger District, this map is useful for delineating target areas for consideration of major preventive treatments. Furthermore, using a GIS, the fire manager can overlay the map of fire occurrence probability with another map showing features of major concern. For instance, if the protection of an endangered species has high priority, overlaying the map of fire occurrence probability onto the map of that species allows the manager to identify critical zones of great fire potential that pose a threat to the endangered species.

Second, the parameters estimated from logistic regressions are useful for evaluating impacts of different variables on the overall fire danger of the entire district. Using the model, one may evaluate the possible change in fire occurrence probability in response to any proposed treatment. For instance, the application of a planned burn to a parcel of great fire potential will not only minimize the fire potential of the burned parcel but also reduce the fire occurrence probability of the adjacent parcels due to neighborhood effects. The extent to which a planned burn will affect the whole district can be estimated from the spatial term of neighborhood effects.

Third, a proposed plan of fire prevention may consist of a combination of several tasks. Using the model of fire occurrence, one can evaluate both the total cost of the plan and the expected effectiveness in reducing the fire potential of the entire district. Alternative strategies can be evaluated objectively and the strategy of maximum cost-effectiveness can be identified (Chou 1992b).

Applications of the model of fire occurrence require that the model be sufficiently flexible for frequent updating in response to changes in environmental, human, and spatial conditions. Each time major changes occur in such conditions, the data must be updated and the model be tested for most current estimation of parameters. In this regard, we suggest that additional efforts be made in updating the data base and expanding the model. Since data entry is the most time-consuming and labor-intensive part of constructing any comprehensive data base, updating usually starts after the database is completed. As the data base of this study was recently completed, we are now ready to obtain additional data and enter them into the database. Most importantly, the fire activity since 1984 must be entered into the data base and incorporated in the model to account for the changes due to these fires.

Furthermore, the model of fire occurrence can be expanded by including additional variables that are relevant to fire behavior and management. At least two variables must be considered: one that relates local winds to topography (Zack and Minnich 1991) and another that reflects the existing preventive treatments. Once these data become available, the same procedure of model building can be carried out again and a more accurate distribution of fire occurrence probability can be obtained.

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