USING GIS GRID AUTOMATION MODEL IN MANAGEMENT DECISION-MAKING AND SUPPRESSION STRATEGY OF WILDFIRES IN A HETEROGENOUS LANDSCAPE

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Abstract

Wildfires are long considered part of the ecology of the forest life-cycle, but uncontrolled wildfires in recent years have devastated prime recreation land, destroyed property and caused loss of life. Though many wildfires are natural in origin, it is increasingly evident that many wildfires are human-induced or at least contributed by human actions. Despite significant progress in forecasting, modeling, fire fighting and emergency response, fires have continued to escalate causing untold damage and losses. The behavior of wildfires has been studied analytically and experimentally for nearly half a century. However, it is in recent decades that the use of remote sensing, Geographic Information Systems (GIS) and modeling have improved our understanding of wildfires. Yet, despite some significant progress, current analytical techniques for wildfire growth prediction fail to address the following issues: (1) neighborhood effects; and (2) influences of probability of fire occurrence on wildfire spread. This study addresses these problems by using GIS, spatial autocorrelation analysis, and logistic regression to create a probability model of fire occurrence and estimate the probability of fire occurrence in the Bee Canyon of San Jacinto Mountain where a major fire occurred in 1996. Based on a grid-based GIS and the empirical fire growth data, a probabilistic grid automation model is constructed to simulate wildfire propagation in an environment of heterogeneous conditions. The grid automation model further incorporates Rothermel's model to estimate the fire spread rate and predict fire spread distribution depending upon predefined time. The simulated patterns of fire spread distribution are compared with the empirical fire propagation data collected from the Bee Canyon fire. The results indicate that the grid automation model could provide useful information to help the management decision making and suppression strategy of wildfires in a heterogeneous landscape.

Introduction

Wildfires are long considered part of the ecology of the forest life-cycle, but uncontrolled wildfires in many parts of the world in recent years (e.g. in Indonesia and Brazil in 1997; in the United States in 1999 and 2000) have devastated prime recreation land, destroyed property and caused loss of life. For example, El Nino conditions in mid-1997 gave rise to devastating forest fires (some natural but most human-induced) that gave brought about significant environmental changes such as forest and habitat destruction, drought, crop loss, regional haze, high temperatures and extremely dry conditions – all culminating in serious health, economic and environmental effects (Chan and Kung, 2000). Though many wildfires are natural in origin, it is increasingly evident that many wildfires are human-induced or at least contributed by human actions.

Wildfire is a natural process that alters landscape structure and creates patch mosaics over the landscape, keeping landscapes in a dynamic equilibrium situation in a large context of time and space (Liu, 1998). Yet, history has shown that many wildfires, if unchecked, could lead to great devastation of resources, ecology and life. Hence, there is the age-old question of whether wildfires should be stopped at all costs, or should they be allowed to play their role in thinning forests. For example, the creation of chaparral mosaics in southern California is the basis of fire control which would reduce the fire size and fires would be distributed more evenly over time and space (Minnich and Chou, 1997). Wildfires also threaten natural resources, endangered species, human lives, and property. Between Oct. 26, 1993 and Nov. 4, 1993, for example, more than a dozen wildfires raged in six southern California counties. Wildfires swept over 200,000 acres of land, destroyed 1,000 homes, and caused damage estimated at 950 million dollars (Facts on File, 1993). In January 1994, cities along the 750-mile eastern coastline of the Australian state of New South Wales were ravaged by more than 150 bush fires. These fires spread over 1.9 million acres of land, destroyed thousands of homes, and cost between 50 million and 100 million Australian dollars (Facts on File, 1994). A fire can be considered either as a prescribed burn, which serves management goals, or a wildfire, which tends to be unwanted and may require certain measures to be taken to control it. If a wildfire shows no foreseeable risk to human life and severe ecological effects, it may be monitored under conditions of prescription. More importantly is the question of how effectively can people respond to wildfires.

Adequate wildfire management decision-making and suppression planning depend on the knowledge and understanding of wildfire behavior, and information on when and where fires are likely to occur which are influenced by weather, fuels, and topology. Fire models can be used to evaluate the probability of a fire spreading into a residential area and the threat to property and lives. Predicted results from fire models could provide an important reference for decision making and management strategies.

However, some fire models are non-spatial models that cannot generate important spatial information for management purposes. In general, non-spatial models require repeated calculations over the long periods of time and cannot provide locational information regarding how a fire spreads, when the fire reaches certain locations, and its growth pattern. In addition, models for fire spread through heterogeneous fuels typically assume that the factors influencing fire spread rates are homogeneous within specified areas (Taplin, 1993). However, fires propagate through landscapes with different types and spatial arrangements of fuels. As a result, it is difficult to predict the spatial pattern of fires efficiently (Rothermel, 1991).

The methods for predicting fire behavior and simulating fire growth under heterogeneous conditions have not been well developed because of technical difficulties in handling complex geographical information in large wildlands. GIS and spatial analysis, however, have made it possible to deal with complicated heterogeneous conditions. Although attempts have been made to integrate fire behavior models with spatially heterogeneous conditions in a GIS, no existing fire growth methods have incorporated two important factors: neighborhood effects and fire occurrence probability.

This research constructs probability models of fire occurrence and grid automation model for fire growth simulation using GIS and incorporating two important factors, neighborhood effects and probability of fire occurrence. This research emphasizes on the spatial modelling aspect of wildfire movement, while incorporating the Rothermel's model for determining the fire behavior characteristics from a heterogeneous environment.

The San Jacinto Mountains and the Bee Canyon Fire

The San Jacinto Ranger District of the San Bernardino National Forest (Figure 1) is selected for this study. The fire history in the district and fire propagation data of the Bee Canyon fire in 1996 provide the necessary data to construct both probability models of fire occurrence and grid automation model for fire growth simulation. The study area, located 150 km east of Los Angeles, California, is dominated by a Mediterranean climate with hot, dry summers and cool, wet winters. Precipitation increases with elevation from 30 cm at Hemet to 70 cm along the crest of the range, then decreases to 10 cm in the desert (Minnich, 1986).

The Bee Canyon fire started on the Bee Canyon road from a southern aspect at 16:47 Pacific Daylight Time, June 29, 1996 at an elevation of 700 m. A total of 3,893 ha were burned between June 29 and July 3 under high temperatures and light winds. This area is mostly covered by the chaparral fuel type, dominated by chamise. The fire propagation map delineating fire spread at different locations and times is given in Figure 2.

A GIS database containing digital data of several variables related to wildfires was established. Among the multiple layers of spatial data in the database, ten coverages were employed in the study. The database is organized into fourteen USGS 7.5-min. topographic quadrangles. Data layers include fire history, vegetation, temperature, precipitation, slope gradient, slope aspect, elevation, roads and trails, man-made structures, and fire propagation data of the Bee Canyon fire.

Neighborhood Effects and Spatial Autocorrelation Analysis

Neighborhood effects represent the influence of entities or features on similar entities in an adjacent area (Chou, 1997). The spread of wildfire is a contagious diffusion process. Hence, neighborhood locations are affected by the same fire phenomena and fire occurrence conditions at one place are related to those of surrounding locations. Therefore, neighborhood effects play an important role in the underlying process and distribution of wildfire.

In this study, the degree to which wildfires are spatially autocorrelated is tested using Moran's I coefficient (Moran,1950), such that

$$I = \frac{n\sum_i \sum_j W_{ij}(x_i - \bar{x})(x_j - \bar{x})}{S_0 \sum_i (x_i - \bar{x})^2}$$

where n is the number of polygons delineated in the coverage. W_{ij} is a measure of the contiguity between polygon i and polygon j. If the value of I is equal to 1, i and j are contiguous; if the value is equal to 0, i and j are not contiguous. x_i equals 1 if the ith polygon was burned and otherwise it equals 0.

A FORTRAN computer program has been developed to extract necessary data in ARC/INFO from the Polygon Attribute Table (PAT) and Arc Attribute Table (AAT) and derive Moran's I and the related statistics for significance testing directly from the attribute tables. The distribution of fires illustrates a positive spatial autocorrelation at a 0.01 significance level, which represents a highly clustered pattern of wildfire distribution.

The contiguity weight is translated into a code of spatial term of neighborhood effects (NBR) from the following formula:

$$NBR_i = \frac{\sum_j W_{ij} x_j}{\sum_j W_{ij}}$$

where NBR is the ratio of the number of burned neighboring polygons to the number of total neighboring polygons. This NBR variable is incorporated in the logistic regression model to explain the distribution of fire occurrence.

The Probability Model of Fire Occurrence Using Logistic Regression Analysis

Fire occurrence probability is defined as the likelihood for major fires to occur in an area. The probability value represents the potential of fire occurrence. This study considers fire occurrence probability as the underlying factors in fire propagation location, because the probability of fire occurrence influences the fire spread pattern and distribution.

In order to evaluate the probability of fire occurrence in an area, it is necessary to construct a probability model of fire occurrence based on the variables that affect the likelihood for fires to occur in that area. Logistic models are based on a sample of n independent observations and each observation is described by p independent variables. The dependent variable y_i is linked to the independent variables through the logistic function (Chou, 1992) such that:

$$p_i = \frac{\exp(U_i)}{1+\exp(U_i)}$$

where p_i denotes the probability value for the th polygon to burn (= 1,2,3,4,,,,n). U_i is a vector product of the form:

$$U_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{3i} + \ldots\ldots + \beta_p x_{pi}$$

where x_{ji} denotes the value of the jth independent variable (j=1, 2, 3, ...,p) for the th observation. β_j is the estimated coefficient of the independent variables x_j. The probability for the th polygon to burn is determined by the quantity U_i which has a value between negative infinity and infinity. A greater U_i implies a higher probability for a fire to take place in the th polygon (Chou, 1997).

The results of the logistic regression include the estimated parameter and associated x^2 and p-value of each independent variables (Table 1). This model has three significant independent variables. The values of these variables, vegetation rotation, July maximum temperature, and the spatial term of neighborhood effects, could be used in the model to calculate the probability of fire occurrence for each study unit.

The Probabilistic Grid Automation Model of Wildfire Growth Simulation

Based on the concept of cellular automata and the empirical data of the Bee Canyon fire, a probabilistic grid automation model is created in GRID module of ARC/INFO GIS using Arc Micro Language to simulate wildfire propagation over heterogeneous environment.

The probabilistic grid automation model is a discrete dynamic system in which states of grids in a regular lattice are updated according to a set of stochastic rules that depend on its current state and the states of its neighbors. In fire growth implementation, each burning cell chooses its next spreading cells depending on the probability value of its neighboring cells.

Based on the probability model of fire occurrence derived from the logistic regression, the probability field of the Bee Canyon was calculated according to the value of significant variables established in GIS. The grid automation model applies the probability field as the basis for simulating the progression of a fire. Based on the basic probability, the grid automation model modifies the probability value for every grid cell in each time step, according to wind direction, wind magnitude, slope gradient, and relative location respect to the burning cell. The magnitude of the weight in the adjustment procedure is calibrated based on partial real time burning data from the Bee Canyon fire of San Jacinto Ranger District in 1996. The higher probability value adjustment indicates greater fire preference.

The probabilistic grid automation model consists of three parts: several 2-dimensional rectangular grids, a template of neighboring cells, and a set of processing rules which determine the burning states of each cell. Grid layers used in this model include probability field, fuel type, elevation, slope gradient, and slope aspect.

Since fire spread is a process of contagious diffusion between neighboring cells, adjacency is the major controlling factor. The neighboring cells are defined as immediate adjacent cells which have the size of eight. The burning status of each grid cell at any time step is determined as a function of the burning status of the neighboring cells at the previous time step. This form can be expressed by equation

$$\boldsymbol{x}_{i,j}^{t+1} = \boldsymbol{f}(\boldsymbol{x}_{i,j-1}^{t}, \boldsymbol{x}_{i-1,j-1}^{t}, \boldsymbol{x}_{i-1,j}^{t}, \boldsymbol{x}_{i-1,j+1}^{t}, \boldsymbol{x}_{i,j+1}^{t}, \boldsymbol{x}_{i+1,j+1}^{t}, \boldsymbol{x}_{i+1,j}^{t}, \boldsymbol{x}_{i+1,j-1}^{t})$$

where $x_{i,j}^{t}$ denotes the value of grid cell i, j at time t. f represents the rule defining the fire propagation. The new state (either burn or unburn) $x_{i,j}^{t+1}$ depends on the previous burning states of eight adjacent cells. For each burning cell in each time step, every neighboring cell from the burning cell is evaluated to decide the fire propagation according to the Monte Carlo method. The Monte Carol method involves taking a set of randomly selected numbers to compare with the adjusted probability value of fire occurrence to simulate the fire propagation.

The advanced model further incorporates the Rothermel's model to calculate the fire spread rate and estimate the fire spread time over each grid cell which is used to delineated possible burned area under predefined period of time. Rothermel's fire spread model (1972) is the basis for most computer-based fire management applications in the United States.

Validation of Modelling Results

The results of fire growth simulation are compared with the real fire propagation data in the Bee Canyon fire in 1996 to validate the probabilistic grid automation model. The approach proposed in the study works reasonably well. From the quantitative comparisons between the simulation results from the advanced model (Figures 3-6) and the empirical burned data, the average percentage-correctly-estimated (PCE) index for polygon one to polygon four is 72% (Table 2) which is better than the results from random estimations for this study to conclude that the grid automation model, which is implemented in the ARC/INFO GIS, can be effectively used to simulate the movement of wildfires over complex terrain and through heterogeneous fuel types.

Conclusions

The probabilistic grid automation model simulates the process of fire propagation according to a set of specified rules based on the probability distribution over space and time. This model could be useful for both fire-related ecological research and empirical wildfire management. The model allows ecosystem managers to visualize the spatial data and simulation results of management and policy decisions. For instance, if the simulated results show that the fire will spread into a developed area, the fire suppression plan should be taken immediately. The simulation results can also be used to determine the most appropriate suppression strategy and design the location of fire breaks and suppression forces. If the simulated results show no foreseeable risk to human life, to endanger species, and to have severe ecological effects, wildfires can be monitored and controlled under the conditions of prescription.

Because wildfire is an important natural force shaping and maintaining the wildland environment, forest, range, and brushland managers may carefully use fire under control in selected situations to effectively manage natural resources (Chase, 1990). The prediction of the rate of spread, intensity, direction, location, and burned area of a wildfire not only enhances over knowledge about ecological processes but also supports wildfire management decision-making.

The information regarding potential fire spread direction, location, and burned area of a wildfire is very important to wildfire management decision making. Since this fire growth automation model implemented in GIS can simulate general fire movement, potential burning area, fire perimeter, and fire behavior characteristics under different fuel, topography, and weather conditions, it could provide the probable consequences of various actions. The fire growth simulation model could be used to answer "what if" scenarios to examine the possible effects of proposed actions and analyze alternative management programs for a given area. Fire managers may apply these spatial-temporally dynamic parameters along with other spatial data to test the possible effects of different strategies. Because it is extremely expensive and difficult to reverse a decision later when applying a fire prescription (Andrews, 1989), potential problems could be screened on the computer before affecting human lives, property, or natural resources directly.

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Table 1. Statistics of the logistic regression model.

Parameter	x^2	p-value
β_0	64.24	0.0000
β_1 (AREA)	0.78	0.3780
β_2 (PERI)	0.51	0.4734
β_3 (ROTA)	17.48	0.0000
β_4 (BLDG)	1.21	0.2715
β_5 (CAMP)	0.00	0.9810
β_6 (ROAD)	2.30	0.1295
β_7 (TEMP)	9.31	0.0023
β_8 (RAIN)	0.17	0.6791
β_9 (NBR)	9301.56	0.0000

Log Likelihood = -112.237
PCE = 99.4

$^{*}x^2_{.05,1} = 10.247$

Table 2. The PCE index from the advanced fire growth model for polygon one to polygon four.

	Number of predicted cell that actually burned / Number of predicted cell	Number of predicted cell that actually burned / Number of burned cell	Average
Polygon one	53.1	94.4	73.8
Polygon two	49.3	100.0	74.7
Polygon three	62.5	47.7	55.1
Polygon four	82.7	83.5	83.1
Average	61.9	81.4	**72**

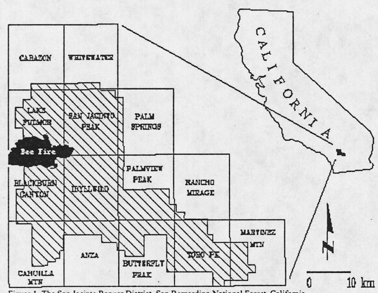

Figure 1. The San Jacinto Ranger District, San Bernardino National Forest, California.

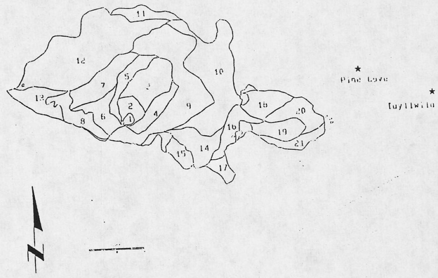

Figure 2. The fire perimeter map with the polygon number delineates fire spread at different locations and times during the Bee Canyon.

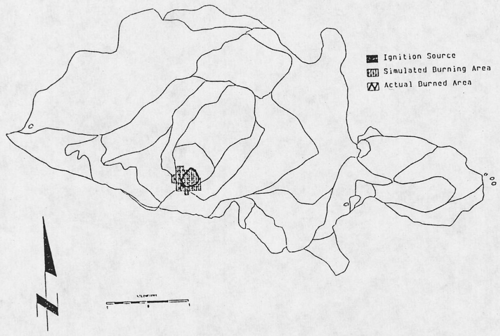

Figure 3 The simulated results for polygon one from the phase II of PGAM. The phase II of PGAM which incorporates Rothermel's model predicts the major fire spread direction and locations accurately despite of the slightly over-estimation in the northwest and southwest areas.

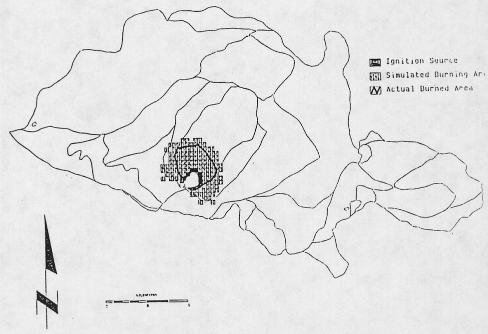

Figure 4 The simulated results for polygon two from the phase II of PGAM. The phase II of PGAM successfully predicts the major fire spread direction, shape, and burned locations in the polygon two of the Bee Canyon fire, except for the over-estimation in the southeast area.

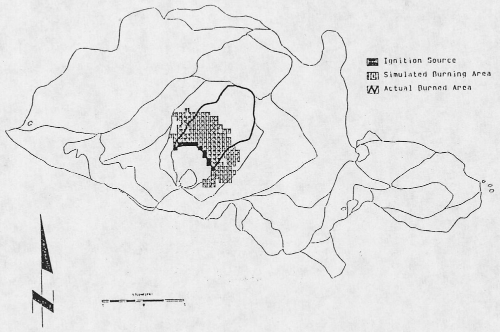

Figure 5 The estimated fire spread direction from the phase II of PGAM for polygon three. The predicted result is the same as the real spread direction of polygon three of the Bee Canyon fire (northeast). However, the burned location on the fire spread direction is underestimated 800 meters and overestimated in the southeast direction 400 meters.

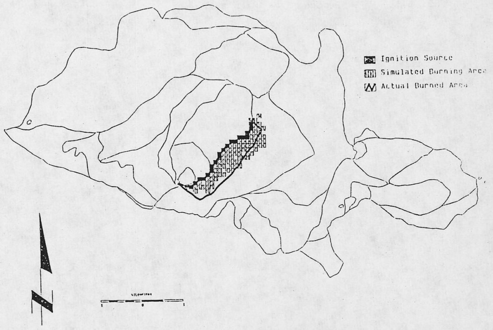

Figure 6 The simulated results for polygon four from the phase II of PGAM under the same environmental conditions. The phase II of PGAM successfully predicts major fire spread direction, shape, burned locations, and fire perimeter in polygon four of the Bee Canyon fire.

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