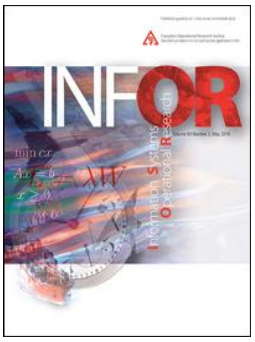

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Abstract — We consider a stochastic fire growth model, with the aim of predicting the behavior of large forest fires. Such a model can describe not only average growth, but also the variability of the growth. Fire is modeled as a random phenomenon on a regular spatial grid, specifically, an interacting particle system modeled as a continuous-time Markov chain on a lattice. Each lattice site changes state according to local transition rates, which model the competing physical processes of fire spread, spotting, and burnout. The rate functions, which are currently tentative, could be based on topography, fuel moisture, and local weather. Implementing such a model in a computing environment allows one to obtain probability contour plots, burn size distributions, and distributions of time to specified events. Such a model also allows the incorporation of a stochastic spotting mechanism.

Keywords lattice model, Markov process, fire spread

1. INTRODUCTION

Modeling forest fire growth is useful for several purposes, including operational fire management, future fire risk assessment, and landscape modeling for management and research. Fire managers use fire growth models for retrospective analysis of past fires, and in real time to aid suppression, safety, and evacuation decision-making (Finney and Andrews, 1999). Spatially-explicit fire risk maps can be produced by, for example, repeatedly simulating the ignition of fires at randomized locations, and their subsequent growth under various weather conditions (Parisien et al, 2005). This can assist strategic protection planning. Landscape-fire models simulate recurrent fire disturbances and vegetation changes in large areas over decades or centuries (Keane et al, 2004), and can be used to determine the natural fire regime for forest management planning, study ecological dynamics, and assess the impact of global warming.

Fire growth models are used to try to simulate realistic fire growth under a wide variety of land, fuel, and weather conditions. Real fire behavior and growth is a complex process that depends on the terrain, the type, arrangement, and dryness of fuels, and current weather conditions. Weather affects fire behavior directly, primarily, by wind, and indirectly through fuel dryness. These factors can vary on a fine scale over space because of fuel heterogeneity and local wind gusts, and over time because of weather. Thus, real fires exhibit spatial and temporal variations that are unpredictable given the data observed at the usual resolutions. Fire perimeters are often irregular with fingers and bays, and under some conditions fires rise into tree crowns intermittently. Deterministic fire growth models may produce unrealistically uniform results, while stochastic models have a better chance of mimicking this irregular behavior.

Whereas a deterministic model will replicate the same fire realization every time, stochastic realizations will differ, as they are driven by different sequences of random numbers. Repeated replications can be used to distinguish likely scenarios from unlikely ones, and to identify relative extremes among the fixed number of replications. With a stochastic simulator, it is possible to obtain probability contour maps.

Berjak and Hearne (2002) give a review of the main types of spread models that have been developed over the past forty years. Trevis (2005) gives a more extensive review. Geometrically, two approaches have been used to model incremental fire growth over a surface: cellular and vector (Trevis, 2005). Cellular models represent the propagation of fire in discrete spatial steps on a fixed grid, changing unburned cells to burned cells. In some models, propagation is by an artificial numerical stochastic process where fire spreads to a particular adjacent cell if a random number exceeds a threshold (e.g., Ratz, 1995 and Li, 2001). The thresholds can be biased

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directionally to simulate the effects of wind, fuel, and terrain. Time is not explicitly represented, and fire growth eventually stops arbitrarily as in the "gambler's ruin" problem. Cellular automata have been used in other ways; Dunn and Milne (2006) give a number of references as well as an interacting automata model which incorporates spatial information such as fuel type, slope, aspect and wind direction.

In percolation models (e.g., Malamud et al, 1998), fuel is either present or absent from individual cells as generated by a simple random process, and fires propagate until they run out of fuel. While these models are stochastic, they do not represent fire behavior or the end of fire growth in a physically meaningful way. Vector models represent the propagation of a segmented linear fire front over a surface, e.g., FARSITE (Finney 2004), Prometheus (Tymstra, 2005 and Richards, 1990). These models are deterministic wave propagation models, although Prometheus has been used stochastically with ensemble techniques, where the deterministic model is run repeatedly with randomly perturbed weather inputs (Anderson et al, 2005); bootstrap methods are also under investigation (Garcia et al, 2006).

In this paper, we present a simple mechanism for incorporating randomness into a fire spread model. Apart from the generic advantages to stochastic simulation given above, our model is, to our knowledge, either the first, or among the first few, to incorporate a mechanism for fire spotting.

Our model is cellular with temporally-explicit and directionally biased propagation rates based on a fire behavior model. The propagation rates from each burning cell to its adjacent cells are explicitly stochastic. Unlike ensemble techniques where the perturbed weather affects all parts of the fire equally, our model has variability among the cells. This represents local variations in controlling factors such as fuel type, fuel density, and wind gusts that exist in reality at resolutions lower than the data available to the model.

Nonetheless, this line of investigation is still in its early stages. We do not propose our model, or stochastic simulation in general, as a replacement for the more popular deterministic models, but rather as a potential future complement to them. Among the many steps still to be performed are the question of the estimation of the parameters used by our model, and future refinements not treated here, to reflect influences such as fuel type and terrain. Our intention is to stimulate the investigation of stochastic fire spread models as a complement to deterministic ones, via the introduction of our model. Our long-term view is that the ideas discussed here may at some point to enhancements to existing deterministic models, or the development of hybrid models which are fundamentally deterministic for fire line growth, but resort to stochastic mechanisms for random phenomena such as fire spotting.

The outline of this paper is as follows. In Section 2, we describe, in detail, the most basic version of the proposed model, including a preliminary model assessment for the case where no covariates are present. In Section 3, we discuss, in broader strokes, how the model can incorporate important covariate information such as wind, fuel type and topography. In Section 4, we describe the fire-spotting mechanism for this model, and in Section 5, we display results of a simulated disturbance in the Turkey Lakes Watershed of Northern Ontario. The paper concludes with a summary and discussion of the many facets of this model that still require investigation.

2. AN INTERACTING PARTICLE SYSTEM MODEL

In this section, we consider the simplest case of our spread model in order to clearly demonstrate the basic mechanisms.

We begin with a flat homogeneous landscape where the weather conditions (e.g. temperature and relative humidity) are constant and there is no wind. The fuel type and density is also assumed to be homogeneous. On this landscape we impose a regular $n \times m$ grid. The grid cells are assumed to be square. We also assume that the nearest-neighborhood of the grid cell (i, j) consists of that cell and those cells immediately to the north, south, east and west, i.e. the set $\{(i, j), (i, j+1), (i, j-1), (i+1, j), (i-1, j)\}$.

At any particular time, each of the nm grid cells can be in one of three possible states: combustible fuel (F), burning fuel (B) or burnt out (O).

To make the model rules as clear as possible, suppose that initially (i.e. at time $t = 0$), cell (i, j) is in state B, while all other cells are in state F. The fire burning in cell (i, j) will spread to its four nearest neighbors in random amounts of time $T_{0,1}$, $T_{0,-1}$, $T_{1,0}$, and $T_{-1,0}$.

At time $T_{0,1}$, the cell at $(i, j+1)$ makes the transition from state F to B, if the cell is not already in state B. Similar transitions are made by cell $(i, j-1)$ at $T_{0,-1}$, cell $(i+1,0)$ at $T_{1,0}$ and cell $(i-1,0)$ at $T_{-1,0}$. These times are assumed to be independent and exponentially distributed with mean $1/\lambda$.

Fuel in a cell starts to burn when there is enough heat in the cell to initiate combustion (Berjak and Hearne, 2002). Our model postulates that if a neighboring cell is already burning, the time until the heat crosses the ignition threshold is exponentially distributed. The Canadian Fire Behavior Prediction (FBP) System (Hirsch, 1996) can be used to choose appropriate values of λ. In particular, we can match $1/\lambda$ with the mean rate of spread predicted by the FBP system (based on the initial spread index (ISI) and fuel type).

Once a cell has made a transition to state B, fire spreads from that cell to the sites of its nearest neighborhood at a new set of independent exponential random times.

A cell in state B transits to state O in another independent exponentially distributed time at rate λ_O. Once in state O, a grid cell will make no further transitions.

The rules of the model are graphically illustrated in Figure 1. Note that the displayed sequence is only one of a large number of possible configuration sequences that can be realized because of the stochastic nature of the algorithm.

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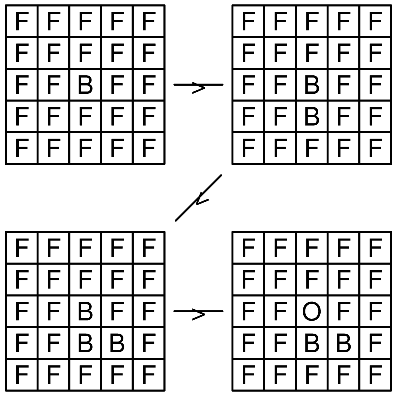

Figure 1. An illustration of the Evolution Rules. The process begins with one burning site (top left diagram). Five exponential random variables are generated (four with rate λ and one with rate λ_O): $T_{0,1}$, $T_{0,-1}$, $T_{1,0}$, $T_{-1,0}$, T_1^O. Suppose $T_{-1,0}$ is the smallest, so fire spreads into the nearest neighbor site to the south of the initial site (top right diagram). The fire at this site can spread to the south, east or west so the time when fire spreads to each of these other sites might be written as $T_{-2,0}$, $T_{-1,-1}$, $T_{-1,1}$. There is also a burn out time T_2^O. Suppose the smallest member of $\{T_{0,1}, T_{0,-1}, T_{1,0}, T_{-2,0}, T_{-1,-1}, T_{-1,1}, T_1^O, T_2^O\}$ is $T_{-2,0}$. Then fire spreads to the southeast (lower left diagram). Suppose T_1^O is the next smallest time. Then the initial site transits to O (lower right diagram).

2.1 Algorithmic Details

When simulating the process, two properties of the exponential distribution are exploited:

1. the memoryless property
2. the minimum of independent exponential random variables is again exponential with rate equal to the sum of the underlying rates

Thus, a discrete event simulation approach can be taken. That is, if there are N burning sites at a particular time T_0,

1. We can simulate a single discrete uniform random variable on $\{1, 2, \ldots, N\}$ to identify the site where the next activity will occur.
2. The time at which the next activity will occur is an exponential random variable with rate $4N\lambda + N\lambda_O$; call this random variable T.
3. The site will transit from B to O with probability
$$\frac{\lambda_O}{4\lambda + \lambda_O}.$$
4. Otherwise, one of the four nearest-neighbor sites is chosen with probability $1/4$ to undergo the transition from F to B. If the chosen site is not in state F, then no change occurs.
5. The clock is updated by adding T: $T_0 + T$, and the above steps are repeated.

2.2 The Four-Point Neighborhood, and the Independence and Exponential Assumptions

Our model is related to the deterministic cellular automata model of Berjak and Hearne (2002), but a significant departure is our use of a four-point neighborhood, instead of the eight-point neighborhood favored by several authors.

The principal reason for use of the four-point neighborhood is its computational simplicity. However, the plots in Figures 2 and 3 suggest that there is little, if any, loss resulting from the use of the reduced neighborhood. According to Huygens' principle (e.g. Richards, 1990), we should expect a fire, under homogeneous conditions, to spread as a circle. However, local inhomogeneities in the fuel as well as the turbulent properties due to the nonlinearity of the fire phenomenon itself are known to cause fluctuations in the actual shape (see, for example, Zhang et al, 1992). The plots in Figure 2 are of two realizations of the proposed cellular spread model under homogeneous fuel and weather conditions.

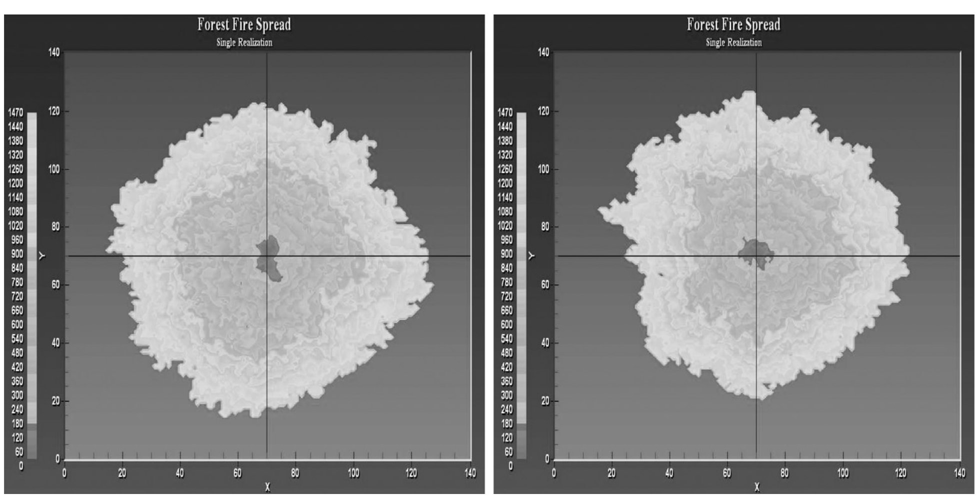

Figure 2. Two realizations of the proposed spread model under homogeneous fuel (Jack Pine), topography and weather conditions (FFMC = 90). Wind speed is 0. These simulated fires have burned for 24 hours. No diurnal variation has been accounted for here.

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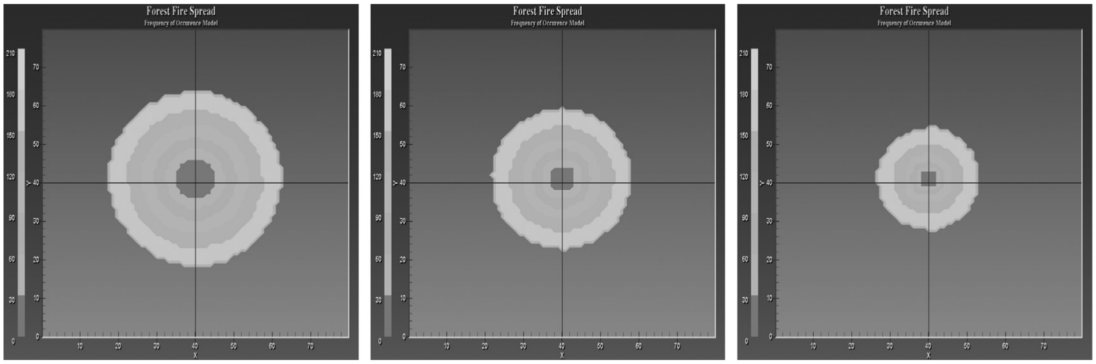

Figure 3. 10, 50 and 90 percent probability contours for simulated fire spread under homogeneous fuel, topography and weather conditions with no wind.

The plots in Figure 3 confirm that there is really no departure, on average, from the circularity expected under the homogeneity assumptions; these plots give 10%, 50% and 90% probability contours. For example, the 10% contour plot colors all sites which burn in at least 10% of the simulated realizations.

Further support for the use of a four-point neighborhood comes from a, perhaps, unexpected quarter. One reviewer raised the question of whether the independence assumption is realistic; is it reasonable to assume that the times to spread from one grid cell to each of its four nearest-neighbors are independent? This is an important question and merits careful consideration, since most conceptual models of a spreading fire involve the idea of a contiguous fire front. This would suggest that the times to ignite grid cells that are spatially near each other will be more dependent than for grid cells that are more remote from each other. Thus, two cells located directly north and west of a given cell, for example, will likely exhibit less dependence than two cells to the north and northwest of the given cell. Thus, use of the eight-point neighborhood may require the use of a form of dependence which we can currently avoid.

In fact, the independence and exponential assumptions that we are making are not inconsistent with the notion of a spreading fire front (in which there are local dependencies), provided the scale of the grid cells is kept fine enough. The stochastic model of the type discussed here is a space-time Markov process. It should be noted that under appropriate re-scaling, diffusion models are generally limits of such discrete state Markov processes. Diffusions are the basis of many differential equation models of physical systems. Diffusions are Markov and as such the past and future are conditionally independent given the present, which is often a reasonable assumption. However since these are re-scaling limits, they do not easily allow for a local dependence. The advantage of a lattice model in this context is that one can incorporate local dependencies.

2.3 Preliminary Model Assessment – A Paper Burning Experiment

Since our work on this model is still in its early stages, we have not proceeded far with the extensive process of validation. However, inspired by the earlier work of Zhang et al (1992), we have done some micro-scale experiments with the burning of paper. Our objective is modest at this point: we aim to show that the basic mechanism of our stochastic model gives a reasonable approximation to the type of shape and growth of a real (though highly artificial) fire in its early stages.

For the Zhang et al article a special light-weight paper was burned; the goal was to study the properties of a flameless burn. They concluded that burning paper shows the same scaling behavior as expected in larger fires. They note that this is perhaps because the fibres which make up a sheet of paper

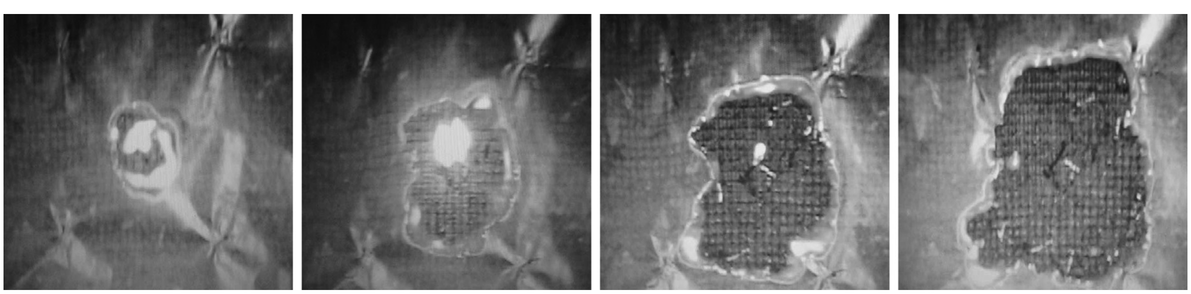

Figure 4. Burn patterns for waxed paper. Observations are taken at 5 seconds, 10 seconds, 15 seconds and 20 seconds.

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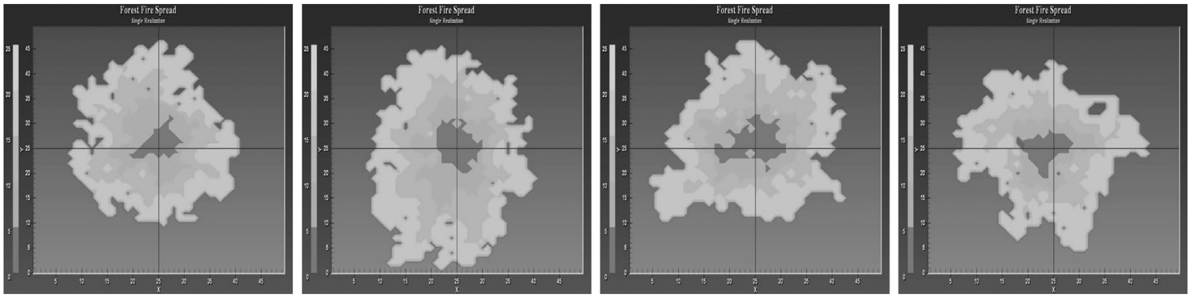

Figure 5. Four simulations of burned waxed paper. The contour levels correspond to burned areas at 5 seconds, 10 seconds, 15 seconds and 20 seconds.

possess the same degree of randomness relative to the size of the paper that the distribution of individual trees of varying densities and orientations possess within the larger forest. Thus, the effect of local inhomogeneities in a paper fire may have the same relative stochastic effect as the local inhomogeneities in a forest fire.

Our objective was not a flameless burn, and in order to keep the amount of smoke to a minimum, we used ordinary waxed paper. This produced a clearly visible fire front. The experiment was conducted in the absence of wind and on a flat surface. A sequence of images from one of the experimental runs is pictured in Figure 5. These pictures were taken at 5 second time intervals following successful ignition of a point at the center of the paper. The irregularities in the patterns are the result of local inhomogeneities – slight differences in slope and aspect, paper thickness and tiny air disturbances.

Cell size was taken to be .005 m (0.5 cm). Since we have not yet developed a systematic estimation methodology for this model (this will, of course, depend upon the type of data actually available), an *ad hoc* approach was taken in order to choose suitable parameter values. In particular, the λ parameter was taken to give an average radial rate of spread of .25 m/minute (.42 cm/s). The rate to burn out for each cell was arbitrarily taken to be $\lambda/6$.

At this preliminary stage, we simply point out the similarity in boundary roughness between the simulations and the experimental fire. Also, the growth in size of the fire over the 20 second period studied roughly matches the growth in size for the simulations. Although this is not strong evidence of the validity of our model, we believe it provides sufficient reason to pursue a more formal investigation.

3. INCORPORATING IMPORTANT COVARIATE INFORMATION

The model for directional rate described in the preceding section is admittedly preliminary. It can, however, readily accommodate more of the great deal that is known from modeling and observation about the physical process of fire spread. This can be done by using, e.g., the Canadian Fire Behavior Prediction System (FBP, Forestry Canada Fire Danger Group, 1992) to give the rate of spread (ROS) as a function of time, fuel type, slope, aspect, wind speed and direction of spread from the propagating cell. The model described in the previous section can be modified to account for these covariates, provided that this information is available at the resolution of the grid in use. Extensions of the model incorporating all of this type of information will be studied in the near future.

In the remainder of the current paper, we assume a homogeneous fuel-type and no impact of topography, but we do consider the effects of varying wind speed and direction as well as diurnal variation. These effects are local level leading to different exponential rate parameters λ and λ_O at each grid cell. Thus, FBP information at grid cell (i, j) gives rise to parameters $\lambda_{(i,j)}$ and $\lambda_{O(i,j)}$.

The rate parameters are also really functions of time. Because of the dynamic nature of wind and weather, it is necessary for the individual exponential rate parameters to vary with time at each grid cell. Let $\lambda^b(t)$ denote the base (ROS) without wind and slope at time t, assuming constant weather, and let $\lambda^m(t)$ denote the maximum ROS with wind and slope. We denote the direction of maximum ROS by $\theta^m(t)$. In flat terrain, this is the wind direction; otherwise, it is the direction of maximum ROS caused by the interaction of wind and terrain (Forestry Canada Fire Danger Group, 1992).

The effect of diurnal weather variation on the ROS can be modeled using a diurnal ROS multiplier, $c(t)$. In principle, this can be modeled from data such as that in Beck et al (2002). For the examples in this paper, we have used $c(t) = 1$, for simplicity.

We can convert the ROS information into the exponential rates required by the model in the following way.

Let

$$\theta_{kl} = \begin{cases} \pi & \text{if } k=0,\ l=-1 \text{ (South)} \\ 0.5\pi & \text{if } k=1,\ l=0 \text{ (East)} \\ 1.5\pi & \text{if } k=-1,\ l=0 \text{ (West)} \\ 0 & \text{if } k=0,\ l=1 \text{ (North).} \end{cases} \tag{1}$$

Adapting a formula of Xu and Lathrop (1994) we use

$$\lambda_{kl}(t) = \frac{c(t)\lambda^b(t)}{1-\cos(\theta_{kl}-\theta^m(t))[1-\lambda^b(t)/\lambda^m(t)]} \tag{2}$$

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as the rate of the exponential time until fire spreads from a burning site to its nearest-neighbor in direction θ_{kl}.

Because the exponential rates change with time, an exact discrete event simulation is more complicated than outlined in the previous section. However, by approximating the rate functions by piecewise constant functions (in time), the algorithm described in Section 2 can be applied with little change.

4. INCORPORATING THE SPOTTING OF NEW FIRES

Modeling the breaching of fuel breaks by fires is of great interest for both fire management and landscape-scale fire simulation purposes. For fire management, natural and artificial fuel breaks are used to deliberately stop fire spread. In landscape fire simulation models, fires must be made to eventually stop growing, either arbitrarily or because of fuel breaks and/or weather changes. For fires in the real world, whether suppressed or not, fuel breaks are occasionally breached by direct heating or spot fires. Factors affecting breaching include the width of the fuel break, the susceptibility of fuel beyond the break to ignition, and aspects of fire behavior including fire intensity, flame length, the wind-driven "tilt" of the leading flames over the fuel break, and fire spotting. Since fire behavior varies over space and time in response to small-scale fuel variation and wind gusts, fuel break breaching can be modeled as a stochastic process.

The fire spread model presented here includes a mechanism to simulate the spotting of new fires. Our algorithm for fire spotting, which is a simplified version of the model by Chase (1984), is described as follows:

1. The occurrence of a firebrand being sent aloft is treated as a competing Poisson event to the rates of spread to adjacent cells and of fire burnout in the existing cell.
2. When a firebrand becomes airborne, its time aloft is determined. This time is currently treated as being exponentially distributed.
3. The likelihood it is still burning or smoldering upon landing is determined. The amount of time that the firebrand burns (or smoulders) is again assumed to be exponentially distributed.
4. Its landing location is determined from a bivariate normal distribution whose mean and covariance structure are functions of the time aloft and the predominant wind direction.
5. Ignition occurs according to a probability which is a function of the fuel type at the landing location.

A number of generalizations can be made to the algorithm. For example, the distributions of the time aloft and time alight can vary with fire intensity, fuel type, and wind speed, and the probability of ignition can be a function of time aloft and local conditions like fuel type and fuel dryness.

In reality, the tendency for firebrands to be sent aloft depends strongly on the fire intensity at the fire front. Similarly, the time aloft, distance traveled, and likelihood of still being alight upon landing are strongly influenced by wind, and future improvements to our model will reflect these facts, among other refinements.

Conversely, the algorithm described above does provide a means for fire to spread to non adjacent cells, and as such, a means for fire to breach non-fuel barriers. In fact, the example we present in the next section shows realizations where fire has crossed a body of water.

It is important to note that most firebrands are never observed, due to failing one of the successive steps leading to a fresh ignition: a) not transcending the boundaries of the existing fire in a perceptible fashion, b) burning out prior to landing, c) not landing on a fuel type, and d) not spotting a new fire despite the capability of doing so. The end result is a highly censored process, which poses a number of statistical challenges when tuning the parameter values.

5. AN EXAMPLE – SIMULATING A DISTURBANCE IN A WATERSHED

We have applied our simulated model to a real landscape located in the Turkey Lakes watershed north of Sault Ste Marie, Ontario. The ignition point was placed slightly southeast of one of the lakes; a southwesterly wind was assumed.

Figure 6 shows that our spotting mechanism has succeeded in spotting new fires due to firebrands being carried over the lake causing ignitions on the northeast side. Figure 7 shows the result of a separate simulation run starting from the same initial conditions.

A comparison of the two figures underscores a fundamental advantage of stochastic simulations over deterministic ones: the capability for the same initial conditions to yield a variety of fire behaviors. Consequently, not only can the mean rate of spread be tracked as with deterministic simulators, but also some sense of the potential variability in shape can be obtained.

Figure 6. Artificial fire spread simulation on the Turkey Lakes Region; duration 2 hr; final fire area 44.50 ha.

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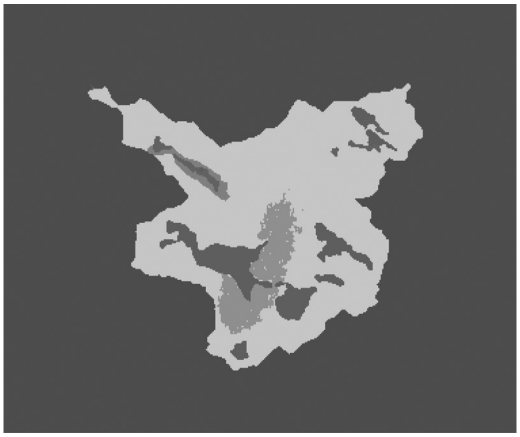

Figure 7. Replicate of artificial fire spread on the Turkey Lakes Region; duration 2 hr, final fire area 95.23 ha.

6. CONCLUDING REMARKS

In this paper, we have introduced a simple stochastic fire spread model. At this time, there are several deterministic spread models in use (e.g. Prometheus, Farsite, etc.). We do not intend for the model proposed here to be thought of as a replacement for these existing models. Rather, we intend to provoke discussion and thought about how to enhance or extend such models using a stochastic spread mechanism.

The model we have proposed is a space-time Markov chain model. The Markov parameters $\lambda_{(i,\ j)}\ (t)$ describe the local dynamics of the system as it evolves over time. It is through these parameters that one incorporates spatial covariate information. These describe local space and time interactions in a similar fashion to diffusion equations, which are space time re-scaled limits of Markov chains. A limiting diffusion does not incorporate interactions at small positive distances, only at infinitesimal distances. A lattice Markov chain allows for interactions at nearby but not immediate neighboring sites. Thus in principle it can model space-time interactions of a similar type to diffusions, plus other interactions that attenuate according to a central limit theorem effect in the diffusion limits. However these lattice processes are generally not as amenable to analytic solution as are some differential equations, and so must be simulated to study specific types of behavior. Much work remains to be done as to how to incorporate physical properties of fire dynamics into the rate functions, using, for example, the FBP system.

There are several natural extensions that one can consider for this simple lattice model. We could modify the state space. For example a lattice site may have states with graduated fuel levels. In that way a site may start burning, then have the fire go out and restart again at a later time. We could use a different distribution for the times between events: in order to retain the Markov property, a natural choice is to use gamma distributions with an integer shape parameter, or perhaps a phase-type distribution. Justification for this is the approximate gaussianity observed for times to burn in at least one experiment (Zhang et al, 1992). This extension can be accommodated by an additional stage associated with the times between jumps, at the expense of longer simulation times. This will not be a serious problem as computing speeds increase.

From literature evaluating deterministic cellular models (Feunekes, 1991), it has been clear that the neighborhood size significantly affects the final size and shape of simulated fires, depending on the angle of the wind relative to the grid. We have found that if the grid size is small enough, rotationally invariant patterns are produced (on average) by our model when using a four-point neighborhood with no wind. Effects in the presence of wind, and effects on final size still need to be studied.

The question of grid size has not been addressed in this paper. When the grid size is too large relative to the size of the study area, the exponential times between changes of state may not be reasonable. However there are space and time interactions, so the times until a fire reaches a specific size may be well approximated using the exponential assumption, but this question is being considered further.

Our model has a mechanism for fire-spotting. It represents fuel break breaching by spotting, but not by direct heating. It may be possible to adapt our model to represent the latter through the use of the spotting mechanism for short distance spotting, i.e., dense spotting on the order of a few meters. A finer landscape grid or compensating calibration may be needed. Alternatively, an explicit direct heating rate process across fuel breaks may be needed.

Finally, it is essential that a comparison be made of the distribution of simulated fire spread rates with experimental fire spread rates in a wide variety of fuel, weather and topographic conditions in order to properly validate this model. In order to do this properly, a systematic parameter estimation technique must be developed, based on the kinds of data that are typically available.

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