Spatial Endogenous Fire Risk

and Efficient Fuel Management and Timber Harvest

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Abstract for "Spatial Endogenous Fire Risk and Efficient Fuel Management and Timber Harvest"

This paper integrates a spatial fire behavior model and a stochastic dynamic optimization model to determine the optimal spatial pattern of fuel management and timber harvest. Each year's fire season causes the loss of forest values and lives in the western US. This paper uses a multi-plot analysis and incorporates uncertainty about fire ignition locations and weather conditions to inform policy by examining the role of spatial endogenous risk - where management actions on one stand affect fire risk in that and adjacent stands. The results support two current strategies, but question two other strategies, for managing forests with fire risk.

Keywords: forest fire, forest management, stochastic dynamic programming, spatially explicit model, spatial endogenous risk, spatial externality

I. Introduction

In recent years, fire has caused significant economic and environmental damage to drier ecosystems in the United States. In Oregon and Washington alone, there are nearly 12 million acres of dry forestland currently at high risk of fire (Agee 2002). This situation appears to be the result of aggressive and effective fire suppression efforts during the last century that have allowed fuel—small trees, bushes, debris, and other undergrowth—to accumulate (Sampson and Sampson 2005) and past harvesting practices that selectively removed fire-tolerant large trees and left small trees with low fire tolerance. When these tinderbox forests do ignite, the resulting high intensity fires can be catastrophic for the ecosystem, in addition to claiming large areas and threatening non-forest areas. The National Fire Plan of 2000 and the Healthy Forest Restoration Act of 2003 recommend active management in the form of mechanical thinning and prescribed fires on federal lands to reduce hazardous fuel accumulation in order to control wildfire within the historical range in terms of size, intensity, and severity (O'Laughlin 2005). Prior to these acts, resources to implement fuel management on public land were limited and little headway had been made. Even with this recent legislation, annual budgets for fuel management on public land are low, making cost-effective allocation of fire prevention effort a particularly timely issue for public land.

Economists have modeled fire risk in forests using nonspatial stand-level models that implicitly assume that actions conducted in one stand do not affect fire risk in adjacent stands. For example, Reed (1984) found that, at the stand level, fire risk acts as a risk premium on the discount rate and shortens the optimal rotation age of a stand. Reed (1987) also considered the optimal protection schedule for fire damage when the rate of fire damage depends on investment in protection. Yoder (2004) extended the Reed models to incorporate prescribed fire as a tool for reducing fire risk. Amacher, Malik, and Haight (2005) modeled planting density, in addition to rotation age and timing of fuel treatments. The volume of salvageable timber was assumed to increase with an increase in fuel treatment efforts and to decrease with planting density. They found that the optimal rotation age can be higher than the Faustmann rotation age for two reasons: (1) fuel treatment cost acts as a planting cost so that increasing rotation age reduces the present value of the infinite series of fuel treatment costs and (2) salvage is a decreasing function of planting density so that less timber volume due to low densities can be offset by a longer rotation age. Although these models have endogenous risk on one stand, they ignore spatial relations between management activities in one stand and fire risk in other stands. Fires commonly move across management unit boundaries, which limits the value of single-stand level analyses. In the forest planning literature, analysts incorporate the spatial movement of fire but omit uncertainty. For example, Sessions et al. (1999) and Hof et al. (2000) model the optimal spatial pattern of fuel management and timber harvest for a particular realization of fire events. These studies do not model the relations between management decisions and the risk of fire damage.

In this paper, we integrate a fire simulation model into a 2-period stochastic dynamic program to search for and analyze optimal spatial allocations of timber harvest and fuel management in the face of spatial endogenous fire risk. By spatial endogenous fire risk, we mean that the spatial allocation of management activities partially determines fire risk. Because fuel management occurs before the fire season, locating that activity requires consideration of both stochastic events—fire ignition and weather—and spatial interactions—fire spread. Here, ignition occurs randomly over the forest but the spatial pattern of forest attributes paired with the spatial pattern of fuel management determine how fire spreads from a particular ignition point. Using a fire simulation model to create all possible fire patterns for all possible decisions, our model's risk-neutral profit-maximizing land manager, in choosing the set of management activities to implement, considers trade-offs between fire risk, timber harvest value, and fuel treatment cost in a spatially explicit way.

This model does not represent a particular case, nor does it represent a general case; we demonstrate our analysis for a range of initial conditions. From the solutions, we draw insights regarding profit-maximizing behavior under the risk of fire. The results inform the spatial focus of fuel treatments, often insuring that no fast fire spread corridors develop but sometimes leaving some high fire spread rate areas untreated. The spatial, multiplot results depict different relations between the optimal harvest age and risk than most single stand analyses and describe situations in which diverse management actions occur on stands that are identical except for their location. Similarly, wind and slope create a heterogeneous risk surface that implies heterogeneous management even in a homogenous forest.

In the next section, we describe the theoretical model, the parameters, and the solution method. That section is followed by a description of the results and a concluding section.

II. The Model

The land manager solves a stochastic dynamic program that condenses the problem into a series of recursive equations. There are m=1,…,M possible states of the initial landscape, S_m^t, that are described by a spatial configuration of stand age and fuel condition at time t. These transition to n=1,…N possible future states, S_n^{t+1}, at the beginning of period $t+1$ depending on the decision vector, D_k^t (a spatial allocation of actions: fuel treatment and harvesting), and stochastic fire events that occur after the decisions are applied in period t. The decision vector represents k=1,…,K possible combinations of actions taken in each management unit (MU) in time period t. In each recursive equation, the land manager must choose a set of actions, D_k^t, applied during period t to maximize $V(S_m^t)$ the net present value of the current period plus the expected maximum net present value of future periods, $V(S_n^{t+1})$:

$$V(S_m^{\ t}) = \max_{D_k^{\ t}} \{v(S_m^{\ t}, D_k^{\ t}) + \beta \sum_{n=1}^{N} P(S_n^{\ t+1}; S_m^{\ t}, D_k^{\ t}, w)\, V(S_n^{\ t+1})\} \qquad \textbf{[1]}$$

where:

$v(S_m^t, D_k^t)$ is net revenue (income from timber harvest less planting and fuel treatment costs) in period t as a function of state m and decision vector k.

β is the discount factor.

$P(S_n^{\ t+1}; S_m^{\ t}, D_k^{\ t}, w)$ is the probability that state n occurs at the beginning of period t+1 for a given state, m, decision vector, k, and weather condition, w, in period t.

In this framework we focus on timber value, as a private forest landowner might. The spatial strategies described here also inform the decisions of many public forest land managers who consider timber values in addition to protecting non-timber forest values from fire damage. To the extent that non-timber forest values are a function of stand age, the public forest land manager's fuel management problem coincides with the results here.

In this model, the probability of a particular fire pattern (e.g. a particular landscape representing a particular spatial arrangement of fuel and vegetation conditions) is computed as:

$$P(S_r^{\ t+1}; S_s^{\ t}, D_k^{\ t}, w^t) = \sum_{w=1}^{W} P_w \sum_{i=1}^{I} \prod_{j=1}^{I} \{\delta_{ij} \cdot \lambda_j + (1-\delta_{ij})(1-\lambda_j)\}\, \{z_{rj} \cdot \gamma_{ij}(S_s^t, D_k^t, w^t) + (1-z_{rj})(1-\gamma_{ij}(S_s^t, D_k^t, w^t))\} \quad \textbf{[2]}$$

where:

P_w is the probability of a weather condition w occurring.

δ_{ij} δ_{ii}=1 and δ_{ij} = 0 for $i \neq j$.

$\lambda_{i,}$ is the probability of fire ignition occurring in stand i.

$\gamma_{ij}(S_m^t, D_k^t, w)$ is the probability of stand j burning when ignition occurs in stand i as a function the state, S_m^t, at the beginning of decision period t, and decisions, D_k^t, applied during decision period t and weather condition w during fire.

Z_n is a vector describing the burn pattern that corresponds with state S_n^{t+1} with z_{nj}=1 if stand j burns, and z_{nj}=0 if stand j does not burn.

The Landscape

To parameterize the model, we used a hypothetical landscape consisting of seven hexagonal management units (MUs) in which one MU is surrounded by six MUs from all directions. This landscape is owned by a risk neutral individual who faces an inter-temporal decision over two 10-year periods. The size of each MU was set so that, given the parameters in a fire simulation model (described below): (1) the whole landscape can be burned only if each MU has fuel conditions that lead to very high or high spread rates and the weather condition is severe and (2) most other combinations of fuel and weather conditions result in fires that spread from the ignition point to at least one other MU. These conditions allow us to illustrate spatial strategies for selectively applying fuel treatment and to avoid extreme outcomes in which all MUs are harvested or no MUs are treated[1].

We constructed a set of initial landscapes with which to demonstrate the effect of spatial fire movement on efficient forest fire fuel management. First, we assume flat terrain and no prevailing wind direction but later relax those assumptions. Second, we assumed that no prior fuel treatment had been applied. This assumption reflects the current situation in many areas because little area has been treated due to limited budgets – especially on public land. This assumption restricts initial fuel conditions to two: untreated young stands with a very high fire spread rate and untreated mature stands with a medium fire spread rate. To limit the number of initial landscapes while allowing spatial interactions between MUs with different fuel conditions, we set young stands to age class 1 (10 – 19 years old) and mature stands to age class 3 (30-to-39 years old). In this forest type, financial maturity in the absence of fire occurs in age class 4 (40-to-49 years old). With two states and no wind or slope (so that mirror images are identical), there are 26 unique initial landscapes, as depicted in Figure 1 (the state variables in the figure are described below).

The Decisions

A decision in each 10-year decision period is a vector indicating which action should be taken in each MU. In the current period, a land manager chooses from four possible actions:

1. harvest (residues are not removed, denoted as "cut"),
2. harvest and fuel treatment (prescribed burning and mechanical thinning, denoted as "cut & fuel"),
3. fuel treatment only (denoted as "fuel"), and
4. grow only (denoted as "grow").

For simplicity, forest fire fuel management occurs only in the current period so that, in the second period, only two actions, "cut" and "grow", are available. Decisions made in the first and second periods reflect a terminal condition in which the management unit's future value is calculated as the present discounted value of harvesting at financial maturity forever – that is, fire beyond the second period is not considered in earlier decisions. Fire events can occur in the current and in the second period after decisions are applied to the landscape

The States

The state of each MU's forest is defined by two attributes, age class and fuel condition. Age class determines timber harvest volume and affects fire spread rate. To insure the empirical relevance of our results, we use timber and fire models that reflect conditions in Oregon's dry, "eastside" forests.[2] Timber harvest volume was projected using the East Cascade Variant of the

Forest Vegetation Simulator (Smith-Mateja 2004). The initial tree list for the simulation was constructed to represent the eastern Oregon dry forest type. We employed ponderosa pine forest type stand data from Malheur National Forest. Age class is incremented by one in each period unless the MU is harvested or burned, in which case age class is set to zero. Because tree growth in each MU is deterministic here, the only stochastic factor in this model is fire disturbance.

Fuel condition, along with stand age class, determines fire spread rate. We used fuel conditions and fire spread rates for untreated stands that were developed by Anderson (1982) and fuel conditions and fire spread rates for treated stands that were developed by Stephens (1998). These fuel models (Table 1) represent typical field situations for Oregon's eastside forests.

In the framework developed here, spatial endogenous risk arises because a management action in an MU changes the fuel condition and, hence, the fire spread rate in the MU depending on the initial fuel condition and age class. Fire spreads faster in young stands than in old stands. Fuel treatment slows the spread rate of fire. As a result, management actions in one MU affect fire risk in adjacent MUs.

The Fire Model

Computation of the probability of transitioning from state S_m^t to state S_n^{t+1} for a given decision vector D_k^t, as defined by Equation (2), requires:

- γ_{ij}, the probability of MU j burning when ignition occurs in MU i. We used a fire simulation model to project fire growth for a given weather condition, ignition point, and spatial pattern of fuel conditions. Fire growth and behavior are modeled using Huygens' principle of wave propagation (Anderson 1982), which is commonly used in fire behavior models such as FARSITE (Finney 2004) and BEHAVE (Andrews 1986). This technique simulates the growth of a fire front as a two-dimensional ellipse wave (Richards 1990). The dimensions of an elliptical wave are calculated using a spread rate that depends on fuel conditions. Fire duration is determined by weather[3]; we assumed that fire duration is 48 hours for moderate weather and 96 hours for severe weather (Graetz 2000)[4]. We define an MU as burned if at least half of the area of the MU is burned[5]. For a given landscape, weather condition, and ignition point, the simulation model is deterministic, making the probability of spread from MU_i to MU_j, γ_{ij} a binary variable equal to 1 if unit *j* burns and 0 if unit *j* does not burn. Simulations for each combination of ignition point, weather condition, and unique initial spatial pattern of fuel conditions that can arise from the 26 initial landscapes after all possible decision vectors are applied define this probability.

- λ_i, the probability of ignition occurring in MU *i*. The fire may ignite in any MU after the current period's decision is made. In this study, each MU has a fixed ignition probability of 0.2 to represent the probability of fire ignition over a decade[6].
- P_w, the probability of weather condition, *w*, occurring. The frequency of different weather conditions during fire events is exogenous. In this study, moderate and severe weather are assumed to occur with probability of 0.6 and 0.4 respectively[7].

Stochasticity of the fire event is captured by a combination of ignition probabilities in each MU and probabilities of different weather condition occurrence. Because there are seven possible ignition locations and two different weather conditions, a set of possible spatial fire patterns is derived from each spatial pattern of fuel conditions.

The Economic Parameters

The specific economic parameters used in this study are within a recent historical range of values. For example, fuel treatment costs range from \$50/acre to \$1,000/acre depending on fuel conditions (USDA 2006); we used a value of \$200/acre. The other values in the model are a real discount rate of 4 %, which represents the real long term productivity of capital as suggested by USDA Forest Service guidelines (Row, Kaiser, and Sessions 1981), a stumpage price of \$500/acre[8], and a regeneration cost of \$200/acre[9]. We assume the landowner is a price-taker so that stumpage price is independent of harvest volume and timber inventory, implying that changes in timber supply from this landscape are too small to affect stumpage price.

The Solution Algorithm

The solution method for this dynamic decision problem under uncertainty involves backward induction. The algorithm first identifies the optimal decision in the second period, D_k^{t+1}, for each state, S_n^{t+1}, by complete enumeration:

$$V(S_n^{t+1}) = \max_{D_k^{t+1}}\{v(S_n^{t+1}, D_k^{t+1}) + \beta \sum_{r=1}^{R} P(S_r^{t+2}; S_n^{t+1}, D_k^{t+1})\ L(S_r^{t+2})\} \qquad \textbf{[3]}$$

where

S_r^{t+2} is one of r=1,…,R possible states occurring at the end of the second period depending on the state at the beginning of the second period, S_n^{t+1}, and the decisions applied, D_k^{t+1}, and fire events occurring during the second period.

$L(S_r^{t+2})$ is the discounted value of the land and standing timber at the end of the second period, t+1, assuming there is no fire and timber standing at t+1 is harvested at financial maturity, the stand is replanted and, again, harvested at financial maturity in perpetuity. Real stumpage price and regeneration cost are assumed to remain constant.

The optimal decision for the current period depends on the expected maximum value in the second period[10]:

$$E[V(S_n^{t+1})] = \sum_{n=1}^{N} P(S_n^{t+1}; S_m^{\ t}, D_k^{\ t}) \cdot V(S_n^{t+1}) \qquad \textbf{[4]}$$

It is computed using the transition probabilities defined by Equation (2). Again, complete enumeration is used to find $V(S_m^t)$ as defined by Equation (1) -- the maximum value of the current period's decision plus the expected maximum value in the second period given the current period's decision, as defined by Equations (3) and (4). The algorithm that solves this problem was written in C and C++ language using Visual C++™ 6.0 (Microsoft Corp. 1995).[11]

III. Optimization Results

In discussing the results, we focus on the impact of two types of spatial externalities on the spatial allocation of fuel management efforts. First, if fire ignites in an MU with a very high spread rate, it is highly likely to spread into adjacent MUs. Hence, the management decision on one MU alters the fire risk facing other MUs—a "spread rate externality". Second, harvesting an MU without fuel treatment increases the spread rate of fire and, therefore, increases fire risk on neighboring MUs—a "harvest externality". As a result of these spatial externalities, land managers face spatial trade-offs that affect the optimal spatial pattern of fuel treatment and the optimal timing of harvest.

To examine the pure "spread rate externality", the model was solved for each of the initial landscapes shown in Figure 1. The optimal decisions for each landscape are shown in Figure 2 and the landscapes resulting from application of the decisions are shown in Figure 3. The landscapes depicted in Figure 3 are subjected to fire events in the current period. Only two of the four management options were selected – "grow" and "fuel." Because no stands reach financial maturity until the second period and there is no constraint on the number of MUs which can be treated, there is no harvest in the current period. If MUs with young stands and very high fire spread rates, "1-VH", are treated, their fuel condition changes to a low fire spread rate, "1-L". If MUs with stands in age class 3 and medium fire spread rates, "3-M", are treated, their fuel conditions change to a very low fire spread rate, “3-VL”.

Some general tendencies can be observed in Figures 1, 2, and 3 with respect to: (1) the treatment of MUs with very high spread rates (“1-VH”), (2) the treatment of the center MU, and (3) the allocation of treatment between MUs with very high spread rates but young trees with little timber value in the current period and MUs with medium spread rates but mature stands (“3-M”) that will likely be harvested in the second period.

First, optimal fuel treatment strategies for “1-VH” MUs fall into two categories: either treat all “1-VH” MUs or selectively apply fuel treatment to insure that treated MUs (“1-L” or “3-VL”) surround all “1-VH” MUs after applying the optimal decision. These treatments result in either eliminating “1-VH” MUs or separating them from each other. Separating MUs with high spread rates reduces the risk of a significant loss of value in multiple MUs because this strategy slows down the spread of fire when fire fronts move into treated MUs. It also reduces the chance that fire will threaten high value timber (age class 3) from more than one side.

Second, the center MU is always treated if it is “1-VH.” If the “1-VH” center MU were not treated, fire ignition from this MU could spread all over the landscape and cause a significant loss of value. When the center MU is “3-M”, deciding whether or not to treat it depends on spatial configurations. For example, in the landscape shown in Figure 2, row 5, column 1, all “3-M” MUs are treated, including the center MU. The “1-VH” MUs are not treated because they are separated on the initial landscape. However, in the landscape shown in Figure 2, row 6, column 4, the “3-M” center MU is not treated, while all of the surrounding “1-VH” MUs are. If the “1-VH” MUs were not treated, an ignition in any one of them would spread through adjacent “1-VH” MUs and fire would attack the valuable “3-M” timber in the center MU from multiple sides, increasing the chance that that MU burns.

The example of not treating the “3-M” center MU also illustrates our third point. There is a trade-off between protection of on-site values by treating “3-M” MUs and prevention of the spread of fire by treating “1-VH” MUs. In a nonspatial model, the incentive to protect nearly mature stands is higher than it is to protect young stands. But in a spatial model, the spread of fire through “1-VH” units can threaten multiple MUs, or threaten valuable MUs from multiple sides, so that the overall loss due to fire on the landscape may be greater if the “1-VH” MUs are left untreated.

To examine the second externality—the harvest externality—and its impact on harvest age, we compared the effect of fire risk on harvest age in a nonspatial model to the effect of fire risk on harvest age in our spatial model. In this forest type and economy, when no fire risk exists or is considered, it is financially optimal to harvest at age class 4. In a nonspatial model, fire risk lowers harvest age because, as Reed (1984) demonstrated, the probability that a stand will burn acts as a risk premium on the discount rate. However, in a spatial model, because newly harvested and young stands have high fire spread rates (Anderson 1982; Huff et al. 1995), harvesting a stand increases fire risk in adjacent stands. This spatial externality causes land managers to postpone harvest in order to reduce risk in adjacent stands.

To illustrate, we define a “threshold risk level” as the level of fire risk (i.e. the probability that an MU will burn) that induces a land manager to harvest at age class 3 rather than at age class 4. In a nonspatial model, using our growth projections, the threshold risk level for a single MU without spatial interdependency is 0.068. If the probability that an MU will burn exceeds that level, the MU will be harvested at age class 3 rather than age class 4. We then solved the spatial model for a subset of 3 initial landscapes (Figure 4A). We selected these landscapes because they illustrate various cases where “3-M” MUs are adjacent to “1-VH” MUs and, therefore, face the risk of fire spreading. We added a constraint to the model limiting the number of MUs that can be treated to one. This constraint ensures that the risk in each MU cannot be reduced to a low level by treating several MUs and forces the land manager to face trade-offs between harvesting and fuel treatment. If, in the spatial model, the threshold risk level for an MU is higher than in the nonspatial model, spatial externalities lead land managers to hold stands longer than they would if they did not consider spatial externalities.

In the 3 solutions, the center MU was chosen for treatment (Figure 4B) and none of the "3-M" units were harvested. That treatment and harvest pattern means that the risk levels in those MUs were insufficiently high to justify harvest at age class 3 rather than at age class 4. The risk levels—the probability the MU would burn—are 0.073, 0.094, 0.115 for landscapes (1), (2), and (3) respectively. These levels exceed the risk threshold in the nonspatial model of 0.068, indicating that a land manager who considers the spatial externality associated with timber harvest will be less likely to harvest timber "early" than one who does not.

In addition, this harvest externality can create a heterogeneous harvest strategy among homogeneous MUs. Without the spatial externality, at high enough interest rates a price-taking land manager will harvest all MUs of a particular, lower age class. With the spatial externality, at higher interest rates, the land manager harvests some but not all MUs at that lower age class. For example, Figure 5B depicts the optimal decisions for the 3 initial landscapes in Figure 5A at a discount rate that induces the spatial land manager to harvest only some of the MUs at age class 3 rather than age class 4. In landscapes (1) and (2), some "3-M" MUs are harvested at the discount rate of 4.6%, while the others are treated without harvesting. In landscape (3), two "3-M" MUs are harvested at discount rate of 4.9%, while one "3-M" MU is treated without harvesting. This heterogeneous harvest pattern within age classes is optimal when spatial interactions are considered because harvesting all valuable MUs without fuel treatment yields a landscape which is prone to larger fires due to connected MUs with high fire spread rates. By treating “3-M” MUs that are adjacent to harvested “3-M” MUs, a land manager can reduce overall fire risk on the landscape.

Wind and Slope

Abiotic factors, such as wind or slope, affect optimal spatial fuel management and timber harvest decisions because they affect the direction and rate of fire spread. To illustrate, we used 8 initial landscapes consisting of four pairs of complements that represent the central spatial characteristics of fuel conditions: homogenous, outside ring, corridor, and patchy. We simulated 4 scenarios: weak wind (5 km per hour), strong wind (40 km per hour), low slope (10%), and steep slope (40%). For the wind scenarios, we assumed that a prevailing wind direction holds during fire events. This assumption reduces the number of possible fire damage patterns because a specific prevailing wind direction leads to a specific fire growth pattern. Wind increases fire risk in the downwind direction and reduces fire risk in the upwind direction compared to the no wind case. The land manager follows a strategy that is specific to wind direction and, therefore, optimal solutions skew in the direction of wind. For the slope scenarios, although ignition probability depends on topographic conditions (Fowler and Asleson 1984; vanWagtendonk 1986; Agee 1993), we maintained our assumption that the ignition probability is independent of slope in order to focus on spatial risk generated from the mechanism of fire spread on a slope. Fire spreads more quickly in an upward direction than it does going downhill. The initial landscapes and the optimal decisions for the two wind scenarios and the two slope scenarios are shown in Figures 6 and 7 respectively.

With weak wind, the optimal strategy dictates harvesting “3-M” MUs that are downwind because they have higher fire risk. Upwind “3-M” MUs with merchantable timber are treated because treatment can reduce overall fire risk sufficiently to justify holding the timber until the financially optimal rotation age. The result also shows that a land manager’s actions become heterogeneous over a homogenous landscape in terms of fuel and topographic conditions. Similarly, with low slope, the optimal strategy is to treat “3-M” MUs at the bottom of the slope and harvest “3-M” MUs at the top of the slope. The center “3-M” MU is more likely to be harvested in the slope case than in the wind case because the shape of the fire is not as elongated as it is when there is a prevailing wind.

For both weak wind and low slope scenarios, treatment of “1-VH” MUs depends on whether there are “3-M” MUs on the landscape. Center “1-VH” MUs are always treated. Downslope and upwind “1-VH” MUs are more likely to be treated than upslope and downwind “1-VH” MUs because fire is more likely to burn into “3-M” units from below and with the wind. When the landscape comprises all or almost all “1-VH” MUs, the upslope and downwind MUs are more likely to be treated because they are most likely to burn if left untreated. “1-VH” MUs at the downwind direction or at the top of the slope may be left untreated even when they are connected; this pattern indicates that a “separation strategy” is not optimal in all locations. Because fire does not spread far in directions perpendicular to the prevailing wind direction or slope aspect , the risk to adjacent MUs located in those perpendicular directions from a high spread rate MU is not large.

When more pronounced abiotic factors – strong wind or steep slope – are considered, the number of MUs treated decreases significantly and the land manager focuses on harvesting merchantable timber. The behavior of fire under strong wind is rarely influenced by fuel treatment (vanWagtendonk 1996; Pollet and Omi 2002; Forest Trust 2004). Hence, the only MUs that are treated are "1-VH" center MUs in Figure 6 because changing the fuel conditions in the center MU from a very high spread rate to a low spread rate reduces the risk of fire damage in multiple downwind MUs. Upwind MUs are left untreated because a strong wind creates an elongated fire following the wind direction, which implies that upwind MUs burn only if ignition occurs in them. The harvest pattern also reflects the strong wind direction and the relative ineffectiveness of fuel treatment in the face of wind. All "3-M" MUs are harvested except the most upwind MU with the lowest fire risk.

The steep slope scenario leads to slightly different treatment patterns than in the strong wind scenario, especially at the bottom of the slope (which is analogous to upwind MUs in the case of wind in terms of a "risk distribution"); the upwind "3-M" MUs are allowed to grow to financial maturity, while the downslope "3-M" MUs are harvested. The difference arises because a steep slope does not create as elongated a fire as does a strong wind; fire that ignites from MUs on the middle of a steep slope may spread downslope to MUs at the bottom of the slope. Therefore, the risk of fire damage in these MUs at the bottom of the slope is higher compared to that in downwind MUs. The results indicate that when the slope is steep, the spatial allocation of fuel treatment may have little impact on mitigating the risk of fire damage because fuel management becomes less effective on a steep slope.

IV. Discussion and Conclusions

This paper extends the forest economics literature by combining: an evaluation of harvest and fuel management decisions on a spatial rather than a single-stand level; a fire behavior model that characterizes spatial endogenous risk; and a model of uncertain fire events rather than assuming a particular type or pattern of fire. This framework forms a platform for evaluating and improving current fuel management to efficiently manage forests at risk of catastrophic fires.

The results here confirm the appropriateness of two commonly pursued management strategies. First, fire and forest scientists often suggest policies that limit the ability of fires to grow, such as policies that create firebreaks between areas of high spread rates (Finney 2001; Hirsch et al. 2001; Finney and Cohen 2003). A non-spatial analysis cannot comment on such policies but instead simply state whether fuel treatment is beneficial on a given plot. The optimal spatial allocation of fuel management derived in this paper confirms this rule of thumb policy because the optimal patterns often follow a "separation" strategy that uses fuel treatments to separate high spread rate forests from each other, thereby limiting the spatial extent of fires. Those treatments may prove optimal in areas that a non-spatial analysis does not treat.

Second, forest managers typically place fuel treatments midway on slopes and perpendicular to prevailing winds to act as firebreaks (N.H Rural Fire Protection Task Force 1995; Finney 2001). Again, single-stand analyses cannot inform such decisions. Our analysis confirms the appropriateness of these policies through the findings about the optimal location of fuel treatment with respect to slope and wind direction. In contrast, consideration of wind and slope yields the somewhat counterintuitive result that the land managers may leave connected areas of high spread rates downwind or at the top of the slope because these abiotic factors create an elongated fire that does not spread perpendicular to the prevailing wind direction or slope.

Our analysis also dispels two commonly held ideas about forest management in the face of fire risk. First, although the Forest Ecosystem Management Assessment Team (FEMAT 1993) proposed to focus treatment on young stands to reduce fire hazard (Committee on Environmental Issues in Pacific Northwest Forest Management et al. 2000), a triage style of determining where to locate fuel management that targets young stands with high fire spread rates often wastes money and effort. Because areas with young trees of little short-term value often have the highest spread rates, whether to treat those areas depends critically on neighboring areas' fuel conditions and timber values. The spatially explicit model determines that the optimal solution lies in between a triage policy that looks just at spread rates and a single-stand perspective that ignores spread rates and simply protects standing timber value.

Second, despite Amacher, Malik, and Haight's (2005) recent study of salvage logging and fuel treatments, traditional forest economics calls for harvesting younger trees in the face of fire risk. Again, this perspective derives from a stand-level analysis. The spatial analysis here shows that because harvesting can increase spread rates and increase risk to neighboring areas, spatial endogenous fire risk increases harvest age when spatial externalities matter. Similarly, this analysis finds that identically stocked areas will be harvested at different times depending on their location and the condition of neighboring areas in an effort to manage fire risk.

Although this stylized framework considers only 7 management units and uses other simplifying assumptions, it provides some general rules of thumb for forest managers. For example, this analysis encourages managers to recognize the impact of actions on one land unit on the risk and appropriate management of other land units—fire's ability to spread implies tradeoffs between protecting an individual management unit's value and protecting a group of management units from fire spread. In addition, the results about the interior management unit here suggest that, in a real forest setting, forest managers should pay special attention to any management units that act as gateways to other management units. Similarly, separating areas of high fire spread rates can prove more important than targeting the highest spread rate areas. Implementation of a "separation" strategy requires the land manager to have flexibility in choosing areas for fuels treatment depending on initial spatial configurations and spatial fire risk generated on them. Therefore, any political or management restriction that constrains the allocation patterns of fuels management efforts may increase the risk of fire damage. For example, Endangered Species Act (1973) limits the area that can be treated, which can conflict with the land manager's objective to mitigate the risk of fire damage.

Recent studies in the forest planning literature that recognize fire spread but assume given ignition points and weather conditions provide a framework for analyzing "what if" scenarios for a particular spatial fire pattern (Finney 2001, Sessions et al. 1999, Hof et al. 2000, Stratton 2004). The land manager will be better-off implementing the resulting fuel management strategy only if that particular fire occurs. If the land manager ignores uncertainty about fire events, the loss to fire could be high if an unexpected fire pattern occurs.

Our framework provides a foundation to research other fire risk management issues. Areas of current research include salvage logging, effectiveness of fuel treatments, tradeoffs between fuel treatment costs and fire suppression costs, non-timber values and fuels management, and ownership patterns. In all of these policy-relevant research questions, as in the basic analysis presented here, the spatial relationships and connections across management units dominate the optimal solutions and lead to different patterns of forest management than derive from stand-level analyses.

Because forest fire suppression policy in the United States has led to an accumulation of forest fire fuel in the last century, fire poses an enormous threat to forest values, particularly in the western states. The limited budgets for preventive measures to mitigate fire loss risk increase the importance of making cost-effective location decisions about fuel management. This paper provides a framework for making those decisions and identifies priorities for managers undertaking those activities.

Footnote

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[1] After some experimentation, we chose an MU size 925 acres. While this is unrealistically large for a timber harvest unit (Oregon forest practice regulations restrict maximum clearcut size to 120 acres (Oregon Department of Forestry, http://egov.oregon.gov/ODF/lawsrules.shtml#rulesubject, accessed August 2006)), it allows us to demonstrate the effect of spatial externalities on optimal fuel treatment. In addition, we consider a ten-year period, which brings this MU size assumption into alignment with 10 years of 120 acre harvests.

[2] Other research performs wide sensitivity analysis on the parameter values used here and describes other types of forests but the spatial results presented here are quite general.

[3] Although fuel moisture contributes to fire growth and can vary with weather, we assume constant fuel moisture for simplicity and because our results are weather-dependent (Hartford and Rothermel 1991, Rothermel et al. 1986, Finney 2004).

[4] To simulate the fire front, 360 points are expanded for the duration of the fire at the spread rate corresponding to the fuel condition of the MU in which it falls using equations developed by Richards (1990).

[5] Fire does not necessarily kill trees. Tree death by fire is a function of crown scorch height and tree diameter (Agee 1993). Under conditions where litter and understory fuel build up due to long fire-return intervals, crown fires with high intensity occur in ponderosa pine type forests (Agee 1993, Pollet and Omi 2002). Because we are interested in cases where fires destroy timber value and causes financial loss for landowners, we only consider cases where fires initiate crown fires, damage trees, and results in total loss of timber value. For a public land manager this scenario could mimic a situation in which a fire removes all timber values because salvage logging following fire is prohibited.

[6] Precise information on an annual ignition probability for specific areas is not readily available. There are studies focused on estimating the risk of fire. Preisler et al. (2004) defined the probabilities of fire for different fire sizes. However, in this study, we used the average fire arrival rate to represent an

ignition probability as studies by Amacher, Malik, and Haight (2005) and Reed (1984). Reed used three different average fire arrival rates, 1%, 2% and 5%. According to Bork (1985) the average fire arrival rate is ranging from around 2% to 6% for ponderosa pine forests in Oregon. We also assume that fuel treatment conducted is effective for the duration of the 10-year decision period. Several studies show that this assumption is reasonable (Loehle 2004, Fiedler and Keegan 2003).

[7] Graetz (2000) examined three weather conditions: wet, moderate and severe. His project's science team suggested that these weather conditions occur with the probability of 0.1, 0.65 and 0.25 respectively based on precipitation data obtained from a weather station in Medford, Oregon. Because we would like to model our case in drier conditions than his study area, we set a higher probability for severe weather conditions and consider only moderate and severe weather conditions.

[8] Stumpage price of ponderosa pine has fluctuated from about \$50/mbf to \$600/mbf (in nominal dollars) between the years 1973 to 1995 (Haynes 1998).

[9] Sessions et al. (2004) estimated regeneration cost to successfully establish 200 conifer trees per acre considering probability of success and cost of restocking failures on different slopes. They report regeneration costs that range from \$250 to \$443 per acre.

10 This formulation assumes that the manager is "foresighted" in that the possibility of adjusting management decisions in the second period in response to the realization of fire occurrence is recognized when current period decisions are being made (Arrow and Fisher, 1974).

[11] The main PC used for computation has dual 3.06 GHz CPU and 2 GB of RAM. Solution run-times were approximately 80 minutes on this main PC. In addition to the main machine, 15 PCs with a 3.4 GHz CPU and 2GB of two PowerMac G5s with dual 2 GHz CPU and 1GB of RAM were used for fire simulation runs.

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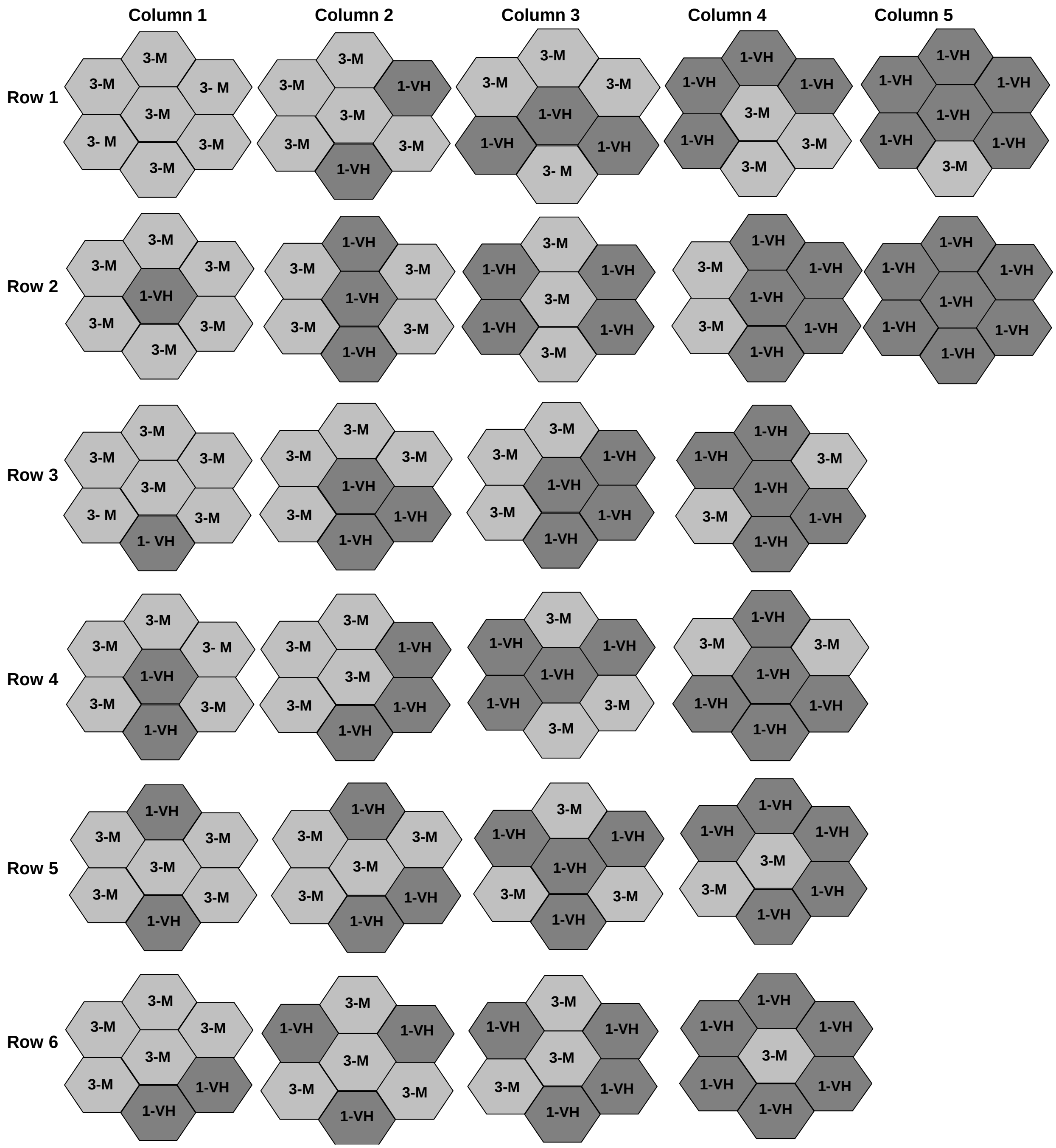
(A) the base model with no slope, (B) low slope, and (C) steep slope.

Table 1: Fuel conditions and fire spread rates used in the fire simulation model.

Fuel Condition	Age Class	Fuel Treatment	Source	Fire Spread Rate (meters per minute)
Very High (VH)	1	No	Anderson (1982)	0.82
High (H)	0	No	Anderson (1982)	0.66
Medium (M)	2 or higher	No	Anderson (1982)	0.35
Low (L)	0 or 1	Yes	Stephens (1998)	0.28
Very Low (VL)	2 or higher	yes	Stephens (1998)	0.18

Figure 1: Spatial configuration of age class and fuel condition for each of 26 initial landscapes at the beginning of the current period. Each MU is labeled “age class – fuel condition.”



Fuel Condition – Fire Spread Rate (Table 1)				
VL = Very Low	L = Low	M = Medium	H = High	VH = Very High

Figure 2: Spatial configuration of optimal decisions for each of 26 initial landscapes in the current period . Each MU is labeled action.”

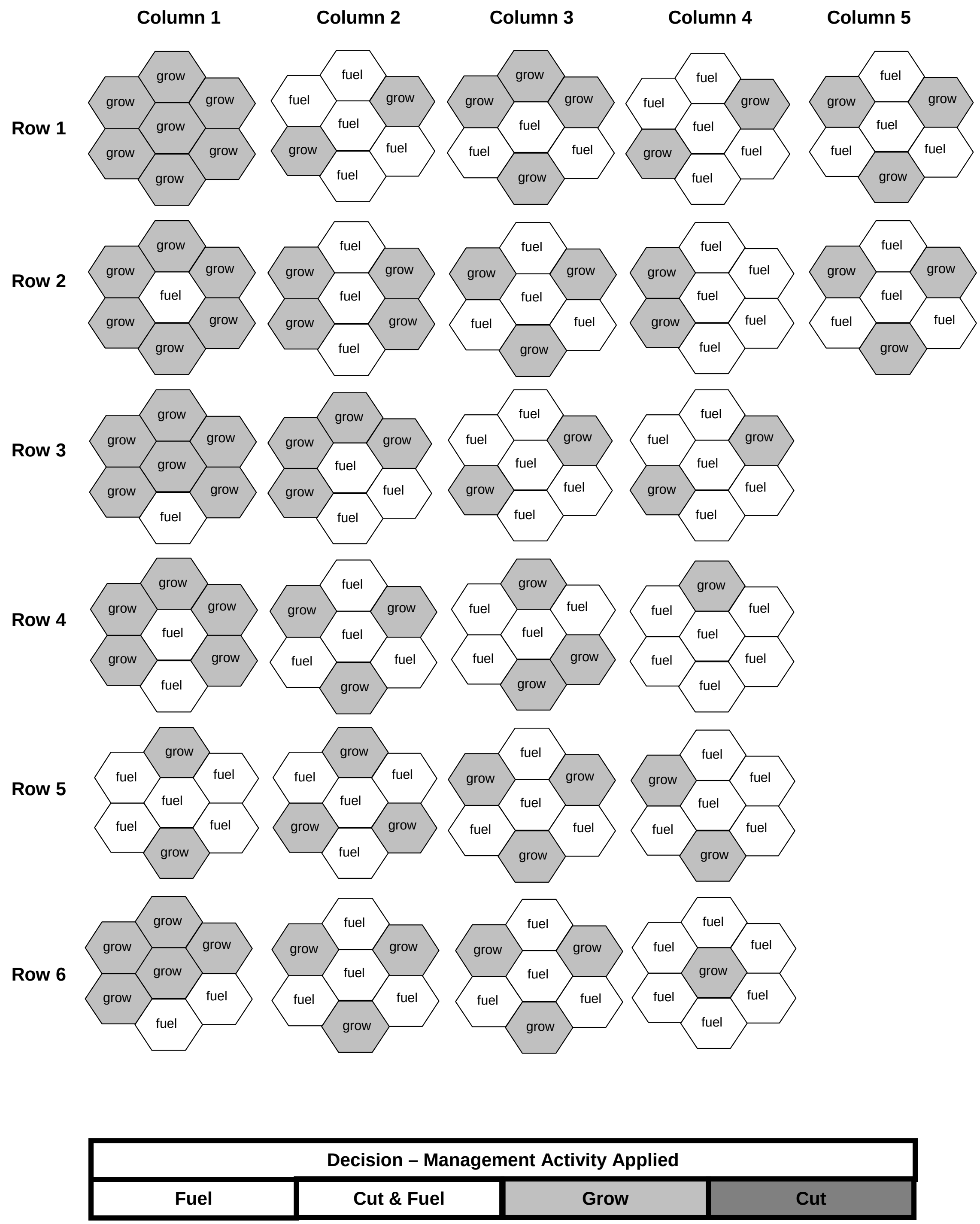
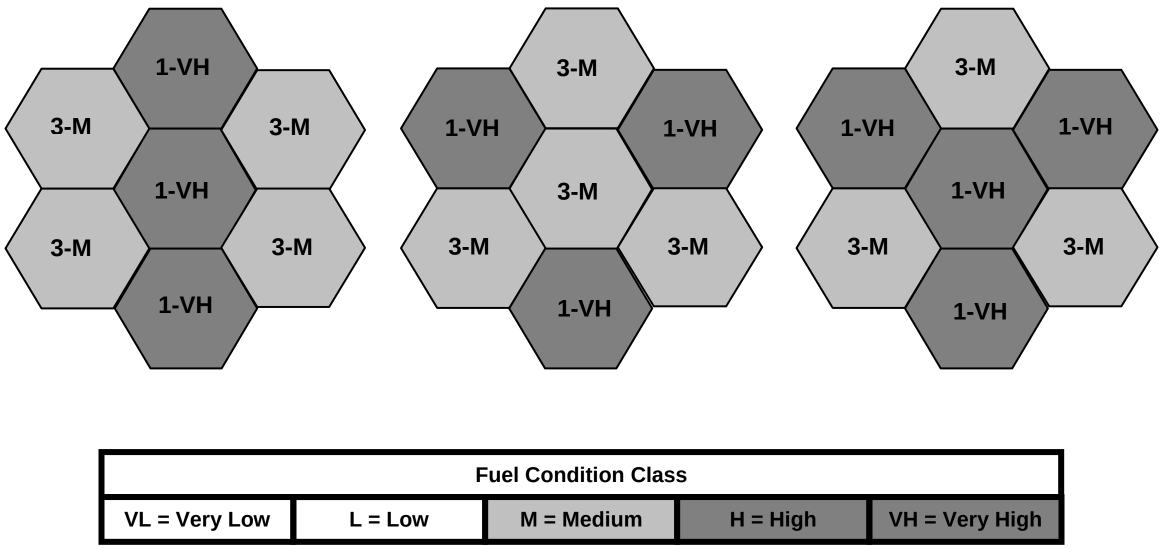


Figure 3: Spatial configuration of age class and fuel condition for each of initial 26 landscapes after optimal decision is applied but before fire event occurs in the current period. Each MU is labeled “age class – fuel condition”.

Fuel Condition – Fire Spread Rate (Table 1)				
VL = Very Low	L = Low	M = Medium	H = High	VH = Very High

Figure 4: Spatial configuration of (A) age class and fuel condition class and (B) optimal decisions for 3 selected initial landscapes used to demonstrate effect of spatial externality on likelihood of early timber harvest. Each MU is labeled (A) “age class – fuel condition” and (B) “action.”

A: (1) (2) (3)



B: (1) (2) (3)

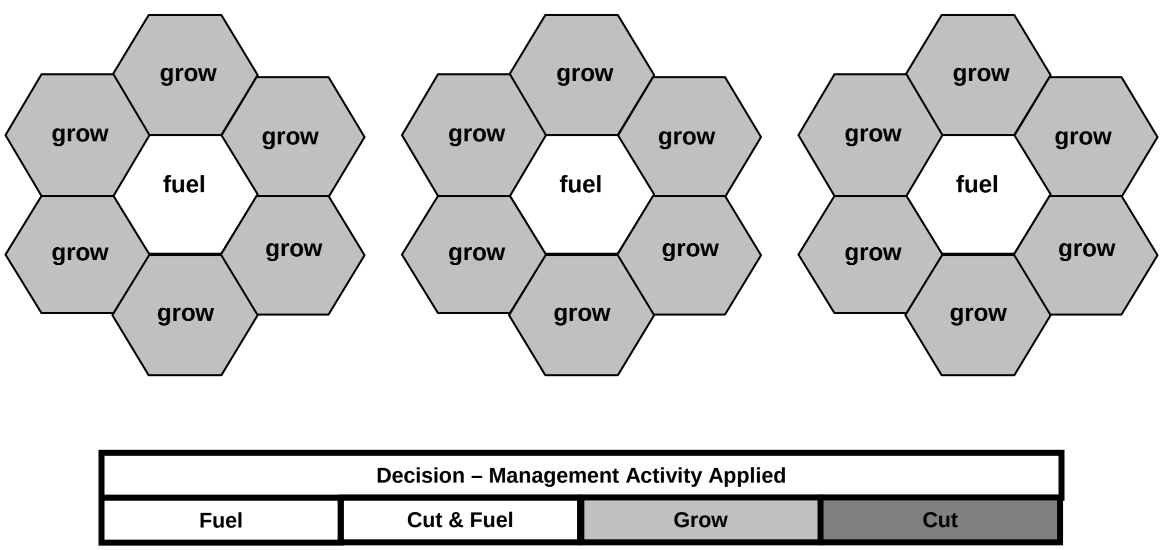
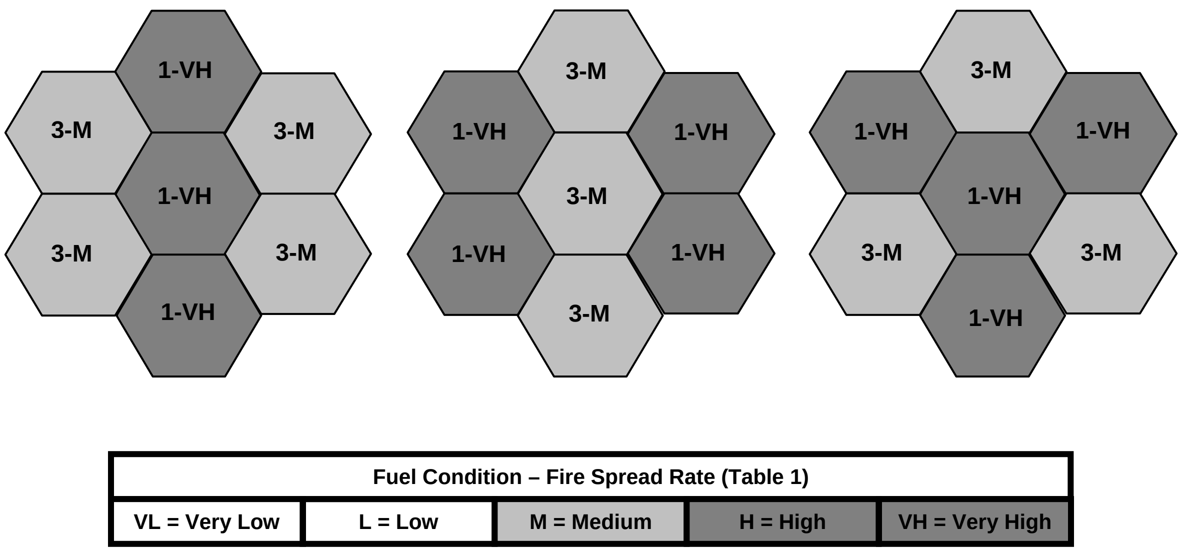


Figure 5: Spatial configuration of (A) age class and fuel condition class and (B) optimal decisions for 3 selected initial landscapes used to demonstrate effect of increasing discount rate on stand age at timber harvest. Each MU is labeled (A) “age class – fuel condition” and (B) “action.”

A: (1) (2) (3)



B: (1) 4.6% (2) 4.6% (3) 4.9%

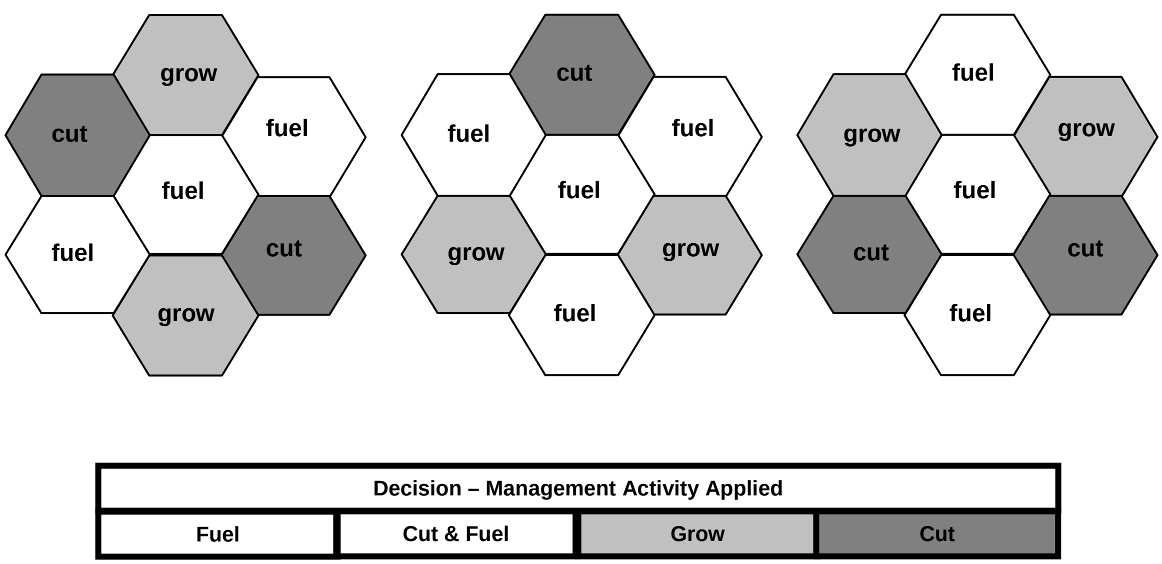


Figure 6: Spatial configuration of age class and fuel condition class for 8 selected initial landscapes labeled “age class – fuel condition” and optimal decisions labeled “action” for (A) the base model with no wind, (B) weak wind, and (C) strong wind.

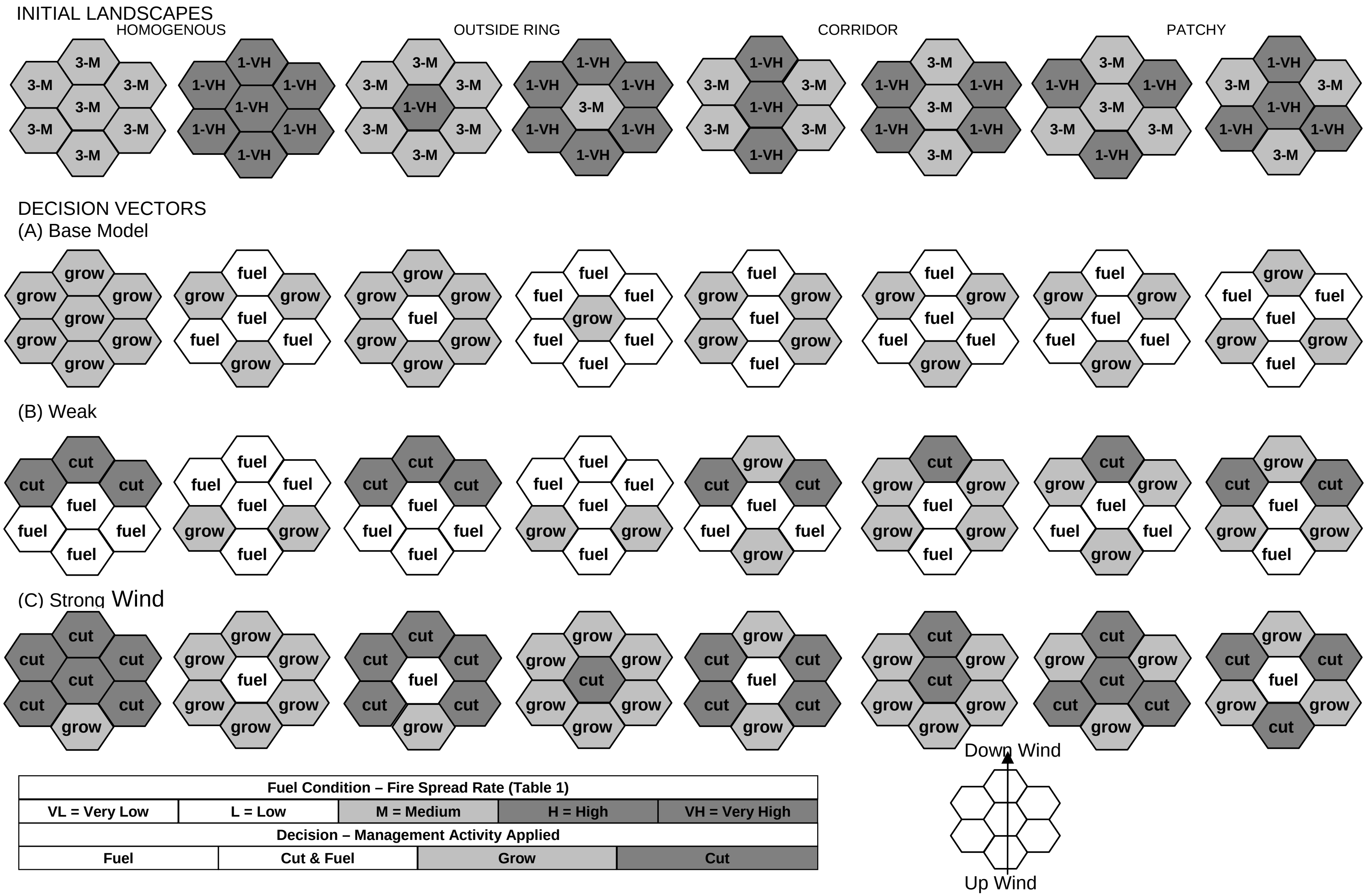
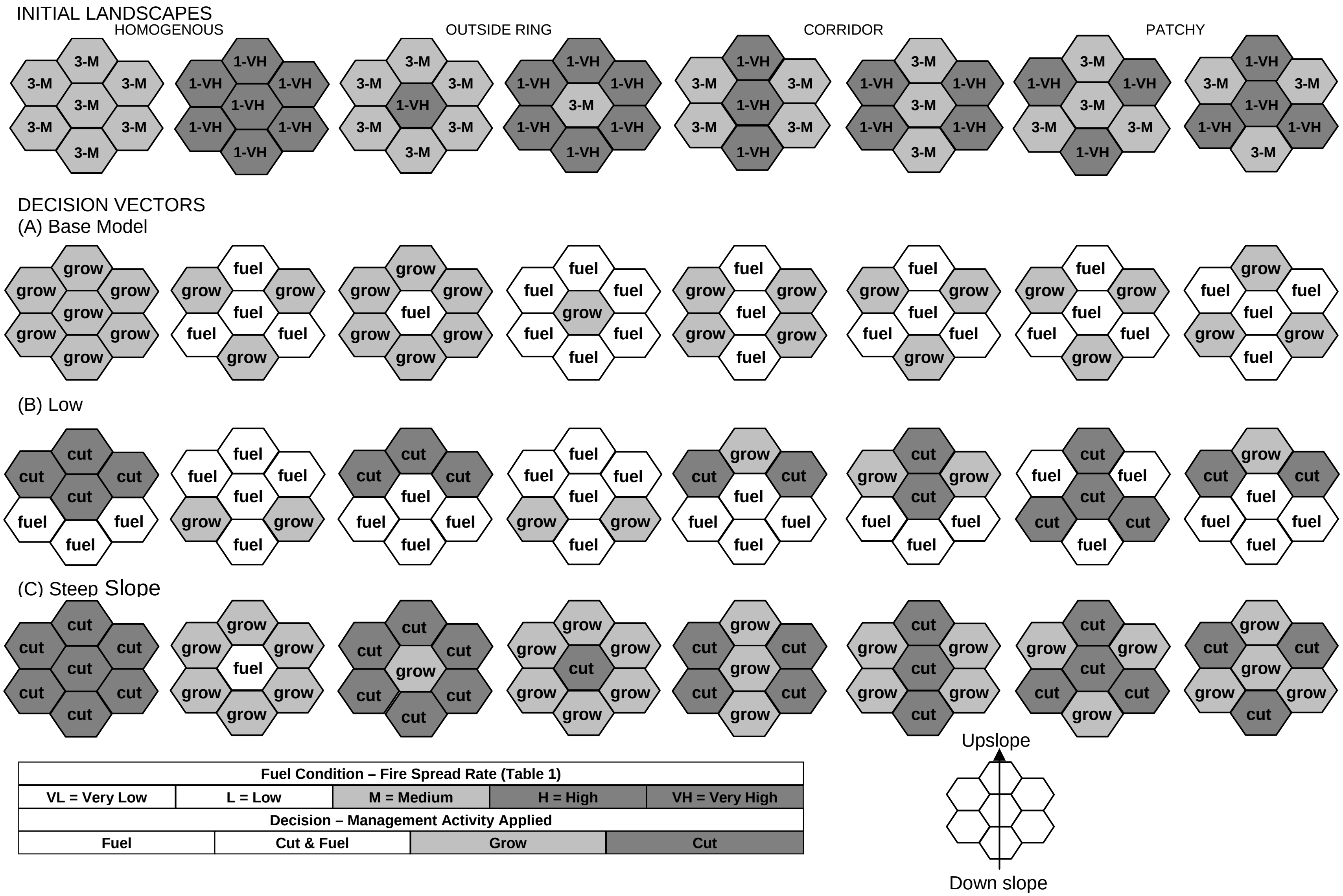


Figure 7: Spatial configuration of age class and fuel condition class for 8 selected initial landscapes labeled "age class – fuel condition" and optimal decisions labeled "action" for (A) the base model with no slope, (B) low slope, and (C) steep slope.



Fuel Condition – Fire Spread Rate (Table 1)				
VL = Very Low	L = Low	M = Medium	H = High	VH = Very High

Decision – Management Activity Applied			
Fuel	Cut & Fuel	Grow	Cut