AN ABSTRACT OF THE DISSERTATION OF

Masashi Konoshima for the degree of Doctor of Philosophy in Forest Resources presented on June 23, 2006.

Title: Spatially Explicit Inter-Temporal Forest Management Decision Under the Risk of Fire

Abstract approved : ______________________________

Claire A. Montgomery Jeffrey L. Arthur

This paper presents a framework for analyzing efficient spatial allocation of forest management efforts - fuel treatment and harvest - under the risk of fire. The framework integrates a fire behavior model and a spatially-explicit stochastic dynamic optimization model. I investigate the effects of spatial interaction across plots during forest fires - in particular a spatial externality - on efficient allocation of fuel management efforts. This spatial externality is captured in a spatial endogenous risk framework - decisions affect a risk distribution over space. By solving computationally for a number of initial bio-economically heterogeneous landscapes, general insight into implementing spatial allocation of fuel management efforts is derived. Sensitivity analyses are conducted to evaluate various economic and physical environments and their impact on the optimal solutions. Because the optimal spatial allocation of fuel management efforts depends on a spatial distribution of "value" and "risk", the decision generated from a conventional dynamic stand level (or aspatial forest level) model or a simple dynamic spatial model can be sub-optimal. Numerical solutions demonstrate that the risk of value loss by fire damage does

not necessarily shorten the optimal rotation age because of spatial externalities. These analyses also show that a land manager faces spatially explicit trade-offs in deciding how to investment in fuel treatments.

Spatially Explicit Inter-Temporal Forest Management Decision Under the Risk of Fire

by

Masashi Konoshima

A DISSERTATION

submitted to

Oregon State University

in partial fulfillment of
the requirements for the
degree of

Doctor of Philosophy

Presented June 23, 2006
Commencement June 2007

Doctor of Philosophy dissertation of Masashi Konoshima presented on June 23, 2006

APPROVED:

Co-Major Professor, representing Forest Resources

Co-Major Professor, representing Forest Resources

Head of the Department of Forest Resources

Dean of the Graduate School

I understand that my dissertation will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my dissertation to any reader upon request.

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ACKNOWLEDGEMENTS

I am indebted to my co-major professors, Dr.Claire Montgomery and Dr.Jeffrey Arthur, for their help, guidance, patience, and encouragement throughout my graduate studies. I express my gratitude to Dr.Heidi Albers for her enthusiasm and helpful guidance throughout the development of this dissertation. Also, I would like to thank the members of my committee, Dr.Andrew Plantinga, Dr.Court Smith and, Dr.Tom Spies, for reading drafts of this dissertation and providing valuable comments. My thanks also go to the members of the College of Forestry Computing Helpdesk for letting me use all computers in computer labs during nights and weekends for computations.

Last, but not least, I express my deepest appreciation to my wife Wako for her support and patience during my years of graduate school. I also want to thank my parents for the many years of support.

This work was supported by funding from the USDA Forest Service Pacific Northwest Research Station and Rocky Mountain Research Station. The research described here does not necessarily reflect the views of the Forest Service and no official endorsement should be inferred.

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1. INTRODUCTION

In recent decades, fire has caused significant economic and environmental damage to drier ecosystems in the US. The US Forest Service spends about 1 billion dollars per year fighting fire. Currently some 10 to 12 million acres of dry forestland are at high risk of fire in Oregon and Washington alone[1]. This situation appears to be the result of aggressive and effective fire suppression efforts of the last century that have allowed fuel - small trees, bushes, debris, and other undergrowth - to accumulate [2]. Past harvest practices (i.e. removing fire-tolerant large trees and leaving smaller trees with low fire tolerance) and policy such as the Endangered Species Act (ESA, 1973) (i.e. few thinning or harvest operations) have contributed to a situation where forests have become highly vulnerable to fire. 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. Land managers and scientists agree that fire risk in these forests should be reduced through active management (e.g. thinning, prescribed burning) [3]. The National Fire Plan (2000) and the Healthy Forest Restoration Act (2003) recommend active management in the form of mechanical thinning and prescribed fires on federal lands to reduce hazardous fuel accumulation. Such active management tools are not intended to exclude fire from a landscape, but rather to control wildfire within the historical range in terms of size, intensity and severity, which is, in ponderosa pine drier ecosystems, relatively low intensity and low severity fires. Even with the recent legislation, annual budgets for fuel management are low, which makes the cost-effective allocation of those budgets all the more timely an issue.

Because fuel management must occur before fire season, determining where to locate that activity requires consideration of both stochastic events - fire ignition - and spatial interactions - fire spread. The ignition point may be random or may be a function of the conditions of a particular stand (or management unit). The spatial forest characteristics paired with the pattern of fuel management determine how fire spreads from a particular ignition point. The risk of fire damage varies over space depending on the spatial arrangement of fuel management [4].

Until recently, models of forest management decision-making under risk of fire have been simple non-spatial or stand (or management unit) level models. For example, Reed [5] studied the optimal rotation age of a stand under the risk of fire using stochastic processes. He showed that the expected optimal rotation age of a stand declined under the risk of fire. However, the implicit assumption of independence across stands does not allow for examination of a situation in which fire can move across management unit boundaries. In addition, fire management decision analysts who incorporate this spatial movement of fire assume a known ignition point [6] [7] - which decouples the spatial decision from the decision under uncertainty.

The model developed here recognizes that the management decisions on one stand contribute to the fire risk facing other stands. The owner of several contiguous stands recognizes the spatial externality generated by actions on one stand: the action taken in a stand will change the spread rate of fire within that stand, which will affect the risk of fire in adjacent stands. In this study, the effects of the spatial interactions are captured in a spatial endogenous risk framework where decisions affect spatial risk.

My model has the following characteristics. First, because fire spreads over a landscape (often spreading to more than just neighboring stands) and because the spatial layout of fuel treatment affects that spread, the commonly used two stand structure does not provide sufficient complexity for my questions.[1] Instead, I employ a landscape large enough to allow interactions beyond adjacent stands.

Second, this study extends previous studies which model optimal time of harvest by including fuel treatment as an option in addition to harvest timing.

Lastly, each decision (i.e. spatial allocation of the management actions) may lead to many different spatial fire patterns because of the stochastic nature (i.e. ignition location and weather conditions during fire event) of fire events.

When this spatial endogenous risk framework is combined with the other two aspects described above, the problem becomes analytically intractable. Therefore, I solve this problem numerically.

In order to derive numerical results, I assume a heterogeneous landscape that is owned by a risk-neutral individual who tries to maximize the expected net present value of the forest resources. A stochastic dynamic programming problem is formulated as a two-period model so that a land manager faces inter-temporal decision of two periods. Fire may ignite in any stand after the current period's decision is made. During a fire event, different weather conditions can occur. Therefore, the stochasticity of the fire event is captured by a combination of ignition probabilities in each stand and probabilities of different weather conditions.

Fire growth from a given ignition point under a given weather condition is projected

[1] For analytical tractability, studies [8] [9] [10] often use two stands to represent a forest in order to investigate the effects of spatial externalities on the optimal rotation age

using a simulation model based on fire behavior models developed by fire scientists [11] [12]. The simulation model identifies how the fire spreads over a landscape in a spatially explicit way depending on the fuel condition and weather. The fuel condition of a stand is determined by a management action (e.g. fuel treatment, harvest) taken in that stand and initial conditions.

The model does not represent a particular case, nor does it represent a general case. However, because the model is flexible I can demonstrate my analysis for a range of ecological characteristics. I attempt to develop a model that provides a systematic, unified framework for explaining some fundamental mechanisms of profit maximizing behavior under the risk of fire. Although the study is primarily illustrative, the model provides us several interesting insights by combining spatial and temporal considerations and explicitly considering the impacts of spatial externality - one stand's condition partly determines the risk of fire on all other stands - on optimal decisions.

Numerical results from my framework demonstrate that the spatial externality leads to several general strategies for cost effective spatial allocation of fuel management. One strategy involves locating fuel treatments in stands to separate two or more stands with very high spread rates. This strategy limits the spread of fire with the treated stand creating a positive spatial externality by limiting risk to other stands. It is not always optimal to treat a "generator" of a large negative spatial externality in order to manage risk across the landscape.

Considering spatial externalities makes the effect of fire risk more complex than in a single stand model. The results show that the risk of value loss by fire damage does not necessarily shorten the optimal rotation age, which may even be lengthened because the standing forest reduces the risk of fire on adjacent stands, as compared to a recently harvested stand. This result occurs because fire spreads faster in recently harvested stand, which has been argued by wildfire scientists [12] [13]. Reed [5] obtained the result that the risk of fire shortens the rotation age assuming the risk that is independent of stand age. However, because he used a single stand model that does not consider the spread of fire, his model did not recognize the negative impact of harvest on adjacent stands, which could shift the rotation age down.

The results indicate that spatial externalities result from a combination of both economic and biological heterogeneity across space and the mechanism of fire growth (fire spread one stand to adjacent stands). The results provide insights into the optimal configuration of fuel management and harvest across homogeneous and heterogeneous (in terms of fuel and vegetation conditions) landscapes, which often treats similar stands differently due to their location.

In order to evaluate the efficiency of results from a spatially explicit optimization model with spatial endogenous risk, I look at the following. First, I consider several "rule of thumb" strategies such as protection of all valuable stands or protection of all stands with high spread rates and compare these objective function values with that yielded from my framework. The "rule of thumb" strategy that yields the highest objective function value can be considered second-best strategies when high transaction costs or lack of information restricts access to the framework developed in this study. The "rule of thumb" strategy ignores spatial interactions. This comparison is made because often priorities for fuel treatment are determined without an explicit consideration of spatial fire growth [14]. I identify the situations where second best solutions will deviate from the optimal one.

Then, I also consider the optimal decision generated from the model assuming a particular spatial pattern of fire damage. Some researchers have developed a framework to find the optimal decision for an anticipated fire pattern. This anticipated pattern is called the "target" fire. However, in this study, the exact spatial pattern of the fire is unknown when a land manager makes a decision in the current period. I evaluate the cost of assuming the "target" fire will occur. I show that the cost could be significantly high if the "target" fire is just one of many possible fires.

The model is also used to analyze the differences between a "foresighted" land manager's optimal decision and a "myopic" land manager's optimal decision. A "foresighted" land manager has the flexibility to adjust his or her decision in accordance with forthcoming information, while a "myopic" land manager does not (a 'myopic" land manager can adjust management in the 2nd period but makes decisions in the current period "as if" there will be no adjustments in the next period). In order to generate information valuable to a land manager, I assume that the supply of timber will change depending on the extent of fire damage. Furthermore, I assume that the price of timber depends on supply. Then, the more stands burned, the higher the stumpage price will become. This price change makes alternative harvest patterns attractive in the event of fire and makes the expected value of information positive.

Because the numerical results described above are derived using a single set of parameters, I conduct sensitivity analyses which investigate various physical and economic environments and their impact on solutions drawn from my model. I vary the parameters one at a time, leaving all others at base values in order to analyze how a single physical or economic factor will impact the optimal decision. I show that harvest strategies become heterogeneous within age classes - that is, not all stands of the same age class are optimally harvested at the same time. This result comes directly from moving beyond an analysis of only one stand toward an analysis of spatial interactions through fire movement and spatial externalities in risk. The analyses identify the nature of important stands and important spatial patterns, which should be protected or maintained. The analysis also demonstrates that the marginal cost of protection depends on initial spatial configurations of fuel conditions and, therefore, the highest cost that a land manager pays for fuel treatment on a single stand (or management unit:MU) varies depending on landscapes. I show that a land manager faces the trade-offs between protection of on-site values and protection of landscapes from the spread of fire when he or she makes a decision of fuel management efforts.

This study focuses on the risk of fire damage that depends on the spatial configuration of vegetation and the spatial configuration of fuel types. I consider spatial patterns of fire caused by factors such as slopes and winds only in the sensitivity analyses section because incorporation of these factors makes the impact of a spatial arrangement of fuel conditions on spatial fire growth unclear. With the previous lack of research on optimal spatial allocation of management efforts, it seems important to recognize how various spatial configurations of fuel conditions will affect the optimal decision. Factors such as winds and slopes are incorporated after I establish a good understanding of the impact of a spatial arrangement of vegetation and fuel types on the optimal decision.

I show that factors such as winds and slopes generate a "heterogeneous risk surface" - a distribution of different risk levels over space - and lead to heterogeneous actions over a homogeneous space (in terms of fuel and topographic conditions). The results also indicate that extreme weather (i.e. strong winds) or topographic (i.e. steep slopes) conditions make fuel treatment ineffective and might result in more harvest.

2. LITERATURE REVIEW

I have developed a framework for cost effective fuel management with spatial endogenous risk. The framework builds on previous research in modeling endogenous risk and spatial interactions. My approach attempts to improve the decision making process within a spatially explicit model and is distinct from previous studies. Development of my framework requires examination and critical analyses of previous studies in forest management under the risk of fire. Therefore, this chapter provides discussion of the literature in three areas: existing models for forest management under the risk of fire damage, spatial models, and endogenous risk models.

2.1. Models for Forest Management under the Risk of Fire Damage

It is possible to classify models of forest management under the risk of fire damage into two groups. One is an optimization model which is often intended to generate the optimal timing of harvest under the risk of fire damage. The other is a simulation model which projects fire behavior and growth for a given scenario (i.e. a spatial pattern of fuel treatment for a given ignition location under given weather conditions).

2.1.1. Optimization Model for Management Decision

Forest management problems under the risk of fire have been extensively studied by formulating problems in optimization frameworks. Most of the earlier studies were either stand-level problems [15] [5] [16] or forest level problems formulated in a non-spatial way [17] [18].

Reed [5] studied the optimal rotation age of a stand under the risk of fire using stochastic processes. He showed that the expected optimal rotation age of a stand shortens under the risk of fire. Boychuk and Martell [18] formulated a multistage stochastic program with recourse for hypothetical data, which represents Ontario's boreal forest. In their study, a dynamic decision-making process under the risk of fire was modeled and recourse actions were allowed. However, their model was aspatial and stochastic fire loss was represented by the proportion burned in each period without identifying fire locations.

These earlier studies built the foundation of forest management decisions under the risk of fire. However, these non-spatial models implicitly assume that the location of management efforts has little impact on the objective value generated for each decision. The action conducted in one stand does not affect the value of adjacent stands.

In the context of fire management, this assumption implies that fuel treatment in one management unit will affect fire behavior only in that unit and has no impact on the spread of fire to adjacent stands. However, fire behaves and grows in spatially explicit ways [14]. Fire spreads from one management unit to the other depending on fuel conditions as well as abiotic factors such as slopes and winds.

2.1.2. Simulation Model

Fire simulation models have been studied and developed separately from optimization models. Most fire simulation models are spatially explicit by definition because the purpose of modeling is to project fire behavior and growth. Fire simulation models do not generate optimal management decisions but do simulate "what if" scenarios.

Forest fire disturbance can be simulated spatially using either mechanistic or stochastic approaches [19]. These two approaches often differ significantly in the time scales simulated as well as other aspects.

Stochastic simulation approaches use probability distributions in combination with random number generators to determine fire events. These approaches have evolved from studies of fire frequency and fire probability developed by Johnson [20]. These models deal with longer temporal resolution or model time step (1-10 years) and use stochastic algorithms to simulate large spatial areas with multiple fire events. Because the temporal resolutions used by stochastic approaches are much coarser than those of mechanistic approaches, detailed fire processes such as lightning-caused ignition or individual fire growth cannot be precisely simulated over time. LADS [21] and LANDIS [22] are stochastic simulation models that use a "cellular automata" algorithm to spread fire as a contagion process between cells of a regular grid. Each cell has a different probability of fire ignition.

Mechanical approaches simulate fire behaviors such as ignition and spread in great detail within a generally short time resolution. Examples include FARSITE [11] and BEHAVE [23]. These are not stochastic models. Both models use Huygen's principle of wave propagation to expand fire fronts. The Huygen's approach differs from a model based on "cellular automata" that spreads fire as a contagion process between the cells of a regular grid. There is no fire probability assigned to each cell. Fire does not grow cell by cell. Models simulate fire behaviors, for given ignition points and weather and wind conditions. Fire growth depends on 1) spread rate, which is a function of fuel types, wind, and humidity and, 2) fire duration time, which is a function of weather.

Because a fire simulation model itself does not tell us about the optimal spatial allocation of management efforts, the simulation model has to be integrated with an optimization model in order to discuss cost effectiveness of fuel management. Examples include [6] and [24], who combined a mechanistic fire simulation model and an optimization model to examine the optimal forest management strategy. In these planning models, stochastic components such as the number of ignition points, locations of each ignition point and weather patterns were provided from the outside of these simulation models

(FARSITE, BEHAVE) using random number generators. These studies based fire size for each simulation run on historical records.

Although these "hybrid" frameworks were developed in order to generate an optimal time path of management action, the frameworks did not explicitly address the interactions between decisions and risks because the optimal decision was identified for a particular realization of fire events.

2.2. Spatial Models

In recent years, more studies have employed a spatially explicit model to analyze forest management problems. Economists have been keeping up with new developments in the natural and biological sciences [25]. In this section, I review papers that develop a theoretical framework for analyzing and searching for the optimal spatial allocation of forest management efforts. Papers reviewed in this section have different assumptions about nature. The simplest spatial model assumes no stochastic events occur. More complex models address endogenous risk. I will also review papers that conduct empirical studies on forest management decisions under the risk of fire damage.

2.2.1. Spatial Interactions and Spatial externality

In this dissertation, a spatially explicit model refers to a model that addresses spatial interactions and spatial externality. In the context of fuel management problems, spatial interaction and spatial externality can be defined as the spread of fire over space depending on fuel conditions on each stand. Therefore, studies that are spatial because they model, for example, the distance from one place to another (e.g. mill location problem) are excluded from our examination of the literature, because spatial interactions and spatial externality are not modeled.

Because forest management is a management of a cluster of single stands (management unit), a land manager considers spatial interactions and spatial externality. For example, habitat for a species often requires a connectivity of suitable habitat. Therefore, actions that disturb desirable forest attributes for a species within a management unit will fragment a habitat. This negative impact of actions has to be considered and evaluated during the search for optimal forest management decisions about wildlife habitat.

As the importance of spatially explicit models in forest management problems has been recognized [26], economists have begun to incorporate spatial aspects of decisions and biological systems into their analyses [27][8]. Swallow *et al.* [8] investigated the effects of spatial externality on the optimal rotation age. A dynamic programming model was used to find optimal harvest decisions for a single owner who manages two management units for both timber and non-timber products. They showed that, even with homogeneous stands, the rotation ages of these two stands might be quite different because of specialization of each stand for different products. However, they assumed no risk and perfect knowledge. The effects of uncertainty on the optimal decision were not considered.

Albers [28] formulated a spatially explicit stochastic dynamic programming problem for the management of tropical forests. Her principle interest was in how irreversibility, uncertainty and spatial interactions affect the optimal land use allocation. Although the decision under uncertainty was addressed in a spatially explicit model, the risk was exogenous in her framework.

Meilby *et al.* [29] modeled endogenous risk in a spatially explicit model for the problem of optimal harvest decisions under the risk of wind-throw. They showed that, due to the sheltering effect of a stand, the optimal rotation age will be prolonged compared with a single stand non-spatial problem, when a forest faces the risk of wind-throw. Although they assumed a hypothetical landscape consisting of four stands, the primary focus was on the effects of a neighboring stand on the timing of harvest. The framework developed in this study is not directly applicable to forest fire management problems because they focused on neighboring effects and timing of harvest. However, this study demonstrated that spatial interactions and spatial externality affects optimal decisions.

2.2.2. Applications to Fire Management Decision Problem

Fire spreads over space and time. Fuel management is intended to mitigate the risk of fire damage by prioritizing the layout of treatment units with an explicit consideration of spatial fire growth. Therefore, recent studies in fire management have tried to represent the problem in a spatially explicit way. Sessions *et al.* [6] developed a spatially explicit forest planning model which considers the risk of high-severity fire. They first generated optimal prescriptions for the planning periods (five 10-year periods) without fire disturbance, then, they simulated a fire disturbance, and adjusted the activities, after the fact, in order to meet the pre-fire goals. Their model allowed for adjustment after a single realization of a stochastic fire event. They did not incorporate risk in their decision making process.

Hof *et al.* [7] developed a one-period spatial optimization model for fuel management problems on a hypothetical landscape. Their model searched for optimal fire control efforts to minimize risk of burning a protected area by slowing a fire front's movement once a fire is ignited. Once a cell is treated then the fire front's movement is slowed down in that cell. Optimization was conducted for different management intensity levels by changing the number of treated cells within the constraints.

In both of these analyses, the optimal decision was derived for a particular realization of fire events. It is unclear how uncertainty will affect the optimal spatial management for fire. More importantly, in these studies, the relationship between decisions and the risk of fire damage was not explicitly modeled. Because decisions of fire management effort affect the probability of fire damage, it is important to consider trade-offs between cost of fuel treatments, returns from harvest, and risk of fire loss.

These trade-offs can be evaluated if feedback loops between decisions and nature (biological circumstances) are established through a spatial endogenous risk framework. Therefore, the interdependency between decisions and risks (spatial endogenous risk) is an important characteristic of the decision making process for this type of problem.

2.3. Endogenous Risk Framework

Endogenous risk has been extensively modeled in many fields other than forest management problems. Shogren and Crocker [30] developed theoretical analysis to derive propositions about the *ex ante* value of reduced risk. Since then, many studies on invasive species have applied an endogenous risk framework [31] [32] [33] [34] . These studies showed that treating endogenous risk as exogenous will lead to an inefficient solution [35].

Although the importance of an endogenous risk framework has been emphasized [36] , only a few studies have applied it to forest management decisions under the risk of fire. Reed [5] modeled the effect of endogenous fire risk on optimal rotation age in the stand-level optimal rotation problem by using a non-homogeneous Poisson process. He assumed that the rate of fire depends only on the age of the stand itself. Adjacent stands were ignored and, hence, the effects of spatial interactions were ignored. Reed [5] also considered the optimal protection schedule for fire damage at a stand level. He assumed that the rate of fire damage varies depending upon the investment level of protection. More recently, Yoder [37] extended Reed's models [5] [38] to a dynamic economic model of prescribed fire use for mitigating the risk of fire damage. Based on the assumption that the risk of wildfire increases with vegetation maturity, Yoder assumed that the longer the time interval between prescribed fires, the higher the risk of wildfire. However, his stand level model did not account for the spatial externality in the decision-making process.

Amacher *et al.* [39], included broader activities such as planting density, in addition to rotation age and timing of fuel treatments. They assumed that the volume of salvageable timber increases with an increase in fuel treatment efforts and decreases with planting density. They found that the optimal rotation age can be higher than the Faustmann rotation age because 1) the cost of fuel treatment acts as planting cost so that increasing rotation age reduces the present value of the infinite series of fuel treatment cost, and 2) salvage is a decreasing function of planting density and the less timber volume due to low densities can be offset by a longer rotation age. However, their model was straight extension of Reed's model and spatial aspects of fire risk and decisions were ignored.

Although, making the risk of fire endogenous at the stand-level is relatively straightforward, modeling spatial endogenous risk can be complicated. In the Meilby *et al.*'s [29] model described above, the risk of wind-throw is endogenous because the risk of wind-throw increases when the neighboring stand is harvested. They assumed a hypothetical landscape consisting of four management units and demonstrated the effect of spatial externality on the optimal rotation age.

My model is closely related to the Melby *et al.*'s [29] model, but differs in some important ways. First, management options for decision making under the risk of fire damage include both harvest and fuel treatment. Spatial arrangement of these actions affects probabilities of particular spatial fire damage patterns (spatial endogenous risk). However, in the study by Melby *et al.*, shelter by a neighboring stand is considered to be the only way to mitigate the risk of damage. Therefore, the study has focused on a small landscape and the timing of harvest. Second, because of the nature of wind-throw damage, Melby *et al.* focused on the effects within neighboring stands rather than spatial harvest patterns. However, within a landscape a single ignition can spread to more than just neighboring stands. Therefore, I employ a landscape large enough to allow interactions beyond adjacent stands. Additionally, Melby *et al.* [29] formulated their problem as an open-loop system, which involves trade-offs between risk of value loss, cost and benefits in the decision making process, but does not guarantee an efficient solution because without feed back , open-loop system cannot take advantage of the forthcoming information. The Melby *et al.*'s study does demonstrate an approach for addressing endogenous risk within a spatially explicit inter-temporal optimization model and, hence, provides a foundation for this study.

2.4. Summary

The literature contains a number of studies that have examined how fire damage affects the optimal decision at the stand level or at the non-spatial forest level. This non-spatial model omits the effect of spatial interaction and implicitly assumes that action in one stand has little impact on other stands. The importance of spatial aspects of forest management has been recognized in recent years. Studies have shifted towards the use of spatially explicit models and away from the use of aspatial models. However, in previous studies which describe spatial aspects of management problems, the dynamic decision making process has been oversimplified by assuming that a particular fire will occur.

This simplification overlooks important components of spatial interactions, namely, spatial endogenous risk. For efficiency, forest management decisions under the risk of fire damage should involve spatially explicit trade-offs between cost of fuel management, risk of fire damage and benefits of harvest. The framework which I developed in this study attempts to improve the dynamic decision making process by applying a spatial endogenous risk framework, while continuing to explicitly address spatial interactions. The research contributes to the decision making literature by providing a framework which can generate cost effective decisions under the risk of fire damage.

3. FRAMEWORK

The contribution of my framework is that it addresses the impact of spatial arrangements of fuel management efforts on the risk of fire damage. This spatial interdependence between decisions and risks - that decisions alter the risk - is called spatial endogenous risk. The land manager uses spatial endogenous risk in a search for the optimal spatial allocation of management efforts, trading offs risks of value loss against costs of fuel treatment and benefits of harvest in a spatially explicit way. In order to incorporate spatial endogenous risk, I integrate spatially explicit stochastic dynamic programming (SDP) and a fire simulation model. The fire simulation generates a set of possible fire patterns for each of all possible spatial configurations of fuel conditions, which result from implementation of all possible spatial allocations of actions (decisions). Each decision leads to a set of different spatial fire patterns rather than one pattern because fire spreads differently depending on ignition location and weather conditions. Output from the fire simulation model is converted to a transition probability matrix - a probability assigned to each passage from a spatial pattern of age class and fuel conditions at t to a spatial pattern of those at $t+1$ - using exogenous stochastic variables (i.e. ignition probability and random weather conditions). A spatially explicit SDP problem is formulated as a two period model by featuring this transition probability matrix. In this section, I first describe a general model for searching the optimal spatial allocation of fuel management effort. Then, I describe a particular parameterizations of the general model, which is used to derive numerical solutions. Before describing the framework, I discuss the concepts of important trade-offs involved in decisions. The following discussion of trade-offs builds the foundation for the arguments in this study.

3.1. Concept of Trade-Offs

There are several important trade-offs involved in the spatial allocation of forest management efforts under the risk of fire. I develop a framework that explicitly addresses these important trade-offs. First, decisions must involve trade-offs across time, which have been extensively studied in the Faustmann rotation literature. The Faustmann formula is the equation that gives us the first-order condition of the optimal rotation age. The formula says that at the optimal rotation age, the marginal value of harvest now must equal the sum of the opportunity costs of the investment tied up in standing timber and the site. Because of the opportunity cost of holding timber, which is represented by a discount rate, the financial optimal rotation age is generally shorter than the biological rotation age (the culmination of mean annual increment) [40]. As discount rate increases, the values obtained in the future become less significant. Therefore, the higher the discount rate is, the shorter the rotation age is. Trade-offs across time are addressed in my framework by modeling a two-period dynamic decision problem.

Reed [5] demonstrates that the optimal rotation age of a stand is shortened under the risk of fire. He found that including an exogenous risk of fire has the same effect on the optimal rotation age as increasing the discount rate. Exogenous risk is not traded off with either costs or benefits because risk of value loss is independent of actions.

Second, decisions involve trade-offs between costs of fuel treatments, benefits of harvest, and risks of value loss because the risk of fire damage depends on fuel conditions, which are controlled by actions (e.g. fuel management, harvest). For a stand-level problem, Reed [5] modeled this endogenous risk for optimal harvest decisions under the risk of fire. He assumed that the risk of fire depends on the stand age. He found that the effect of fire on the rotation age becomes more complicated by making risk endogenous because the action taken can influence the probability of a fire.

In an endogenous risk framework, the risk of fire damage can be reduced through fuel treatments. Because fuel treatment is costly, a land manager will accept some level of risk at different costs of fuel treatments. Therefore, decisions involve a comparison of the cost of fuel treatment and the expected benefits of that treatments, which includes assessment of the risk of fire damage at the site and the benefits that can be obtained from the site if no fire occurs. The optimal condition for investment in fuel treatment requires the marginal increase in the expected net present value (NPV) of the site to be equal to the marginal cost of fuel treatment. An increase in the expected net present value of the site occurs in two ways: increasing the value of the site; and reducing the probability of fire at the site. Also because harvest is an option, sometimes harvest will be chosen over fuel treatment, when, for example, the risk of fire damage is high.

Although in the forest fire management literature there have been only a few studies modeling endogenous risk, it has been extensively studied for other issues such as invasive species [31] [32] [33][34] . These studies demonstrate that treating endogenous risk as exogenous leads to inefficient solutions. Without an endogenous risk framework, a decision maker cannot choose the acceptable level of risk by explicitly taking into account tradeoffs involved in decisions. In my framework, these trade-offs are explicitly addressed by applying a stochastic dynamic programming (DP) formulation. By modeling links between possible decisions and possible states resulting from implementation of each decision using a transition probability matrix, a stochastic DP formulation addresses endogenous risk.

Lastly, decisions involve trade-offs between MUs, which are addressed by formulating a spatially explicit dynamic optimization model in my framework. Decisions involve comparisons of values obtained in one MU and values obtained in the other MU. A land manager has more incentive to assign fuel treatment on valuable MUs than MUs with non-merchantable timber because the benefits of protection of valuable MUs are higher than those of MUs of a young age class. Therefore, a land manager behaves over space in response to relative profit opportunities [41].

However, sometimes, a land manager finds it is better to leave valuable MUs untreated. There are two cases in which a land manager leaves (a) valuable MU(s) untreated. First, when the marginal increase in the expected NPV from protection of a valuable MU does not exceed the additional cost of fuel treatment, this valuable MU will not be treated. This condition is already explained above. For a non-spatial model, this condition determines the optimal investment level of fuel management.

Second, even if this condition is met, there could be a different spatial arrangement of management efforts (including both harvest and fuel treatment) that yields a higher expected NPV. A land manager searches for a cost-effective spatial allocation of fuel management, which yields a large reduction of the risk of fire at a small cost or a large increase in the expected NPV at a small cost. For example, the management decision maybe cost-effective if treating a single MU reduces the risk of fire damage in many MUs. Therefore, it is not always true that treating all valuable MUs is the most cost effective plan.

The latter case leads us to the concept of trade-offs between on-site value protection and prevention of the spread of fire. For developing the concept of these trade-offs, two factors, "value" and "risk", are critical for determining the optimal spatial allocation of management efforts. As I mentioned above, valuable MUs are more likely to be treated in a landscape consisting of MUs of different age classes. This heterogeneous "value" over space - "heterogeneous value surface" - creates an incentive for allocating fuel management efforts over space.

However, a land manager also treats MUs with very high spread rates, which are often not valuable, because if an MU with a very high spread rate is left untreated, an ignition from this MU will damage this MU itself, spread to adjacent MUs and increase the risk of fire damage not only in this MU but also in adjacent MUs. Therefore, leaving these MUs untreated may reduce the expected NPV significantly. "Not treating" an MU with a very high spread rate will produce a spatial externality, impose a risk in adjacent MUs and create a "heterogeneous risk surface" - a distribution of different risk levels over space - which operates to allocate fuel management efforts to distribute the risk of fire damage over space. These two factors of a "heterogeneous value surface" and a "heterogeneous risk surface" operate together and determine the cost-effective spatial allocation of fuel management efforts. In some spatial configurations they operate in a complementary fashion, and in other spatial configurations they work against each other. Therefore, a land manager's decision involves comparison of values obtained from treating valuable MUs (on-site value protection) and values obtained from treating MUs with high spread rates (prevention of the spread of fire). Depending on initial spatial configurations of fuel conditions, prevention of the spread of fire yields higher or lower value than on-site value protection. A land manager may mix these two schemes of decisions to yield a higher expected NPV.

The concept of the spread of fire cannot be addressed in a non-spatial model. Only protection of on-site value does matter for a stand level model or non-spatial model. This concept of spreading is closely related to the concept of spatial externality. A spatial externality is the impact on other MUs of an action in a particular MU (or patch, stand). In this study, the action taken in an MU will change the spread rate of fire, which will affect the risk of fire damage in adjacent MUs because a high spread rate allows fire, which ignites from a particular MU, to move into and damage adjacent MUs. These spatial externalities are captured in a spatial endogenous risk framework.

In my framework, the trade-offs explained above do not occur independently. Because spatial endogenous risk is modeled, the framework allows me to evaluate a land manager's decision that involves tradeoffs between costs, benefits, and risks of value loss in a spatially explicit way. Decisions involve comparisons of spatial arrangements of fuel treatment in terms of costs, benefits and risks yielded from each spatial arrangement. In my framework, a land manager accepts a certain level of risk in each MU by comparing the cost effectiveness of different spatial arrangements of management actions.

3.2. General Model

I represent the problem facing a land manager when management actions can affect the spatial patterns of fire as a stochastic dynamic programming (SDP) problem. SDP condenses a land manager's problem into a series of recursive equations. In each recursive equation, the land manager must choose a set of actions (a spatial allocation of actions: fuel treatment and harvest) to maximize the net benefit of the current year plus the net present value (NPV) of future years.

A decision in each period is "which action should be taken in each MU" (a spatial allocation of actions) and it can be represented by a vector of actions. A decision, k, or a set of possible actions, D_k^t, is made up of actions d_{ik}^t where i denote a management unit id and t denote time. Each of all possible initial landscapes, m=1,.,M, which shows a spatial configuration of stand age and fuel condition at the beginning of 1st period, transitions to possible landscapes, n=1,.,N at the beginning of the second period depending on decisions applied and stochastic fire events.

The SDP equation is:

$$V(S_m^t) = \max_{D_k^t}\{v(S_m^t, D_k^t) + \delta \cdot \sum_{n=1}^{N} P(S_n^{t+1} \mid S_m^t, D_k^t) \cdot V(S_n^{t+1}) \tag{3.1}$$

Where

S_m,S_n: the state describes the spatial configuration of stand age classes and fuel conditions depend on past harvest, fuel treatment, and fire events.

D_k^t: decision k, a vector of fuel management efforts and harvest, in period t

v(S,D): net revenue in period t is function of state and decision.

δ: discount factor

$P(S_n^{t+1};S_m^t,D_k^t)$: the probability of state n occurs at the beginning of the 2nd period for a given state m and decision variable D_k^t in the first period.

In this model, $P(\cdot)$ is computed as:

$$P(S_n^{t+1}; S_m^t, D_k^t) = \sum_{w=1}^{W} P_w \sum_{i=1}^{I} \lambda_i \cdot \prod_{j \neq i} (1 - \lambda_i) \prod_{z_{ni}=1} \gamma_{ij}(S_m^t, D_k^t) \prod_{z_{ni}=0} (1 - \cdot\gamma_{ij}(S_m^t, D_k^t)) \qquad (3.2)$$

Where

P_w: the probability of a weather condition w occurring,

λ_i: ignition probability of fire in stand i,

$\gamma_{ij}(S,D)$: probability of unit j burning when ignition occurs in unit i as a function of initial state, S, and decisions, D, made by the land manager.

Z_n: a vector describing the burn pattern that corresponds with state S_n with z_{nj} = 1 if unit j burns, and z_{nj} = 0 if unit j does not burn

3.3. Base Case Parameterizations

I represent the system as simply as possible, due to the complicated nature of the problem, which is combinatorial and stochastic, while keeping the system descriptive enough[2] so that insights regarding optimal spatial management allocation can be drawn. A hypothetical landscape (Figure 3.1) is assumed to consist of seven hexagonal management units (MUs), which are owned by a risk neutral individual who is facing an inter-temporal decision about two periods. In this landscape, one MU is surrounded by six MUs from all directions (Figure 3.1). I assume homogeneity within each MU in terms of fuel and vegetation conditions. In the base case, the landscape is flat and there is no wind.

The size of a hypothetical landscape is chosen so that analyses of cost effective spatial allocation of fuel management can show interesting insights (e.g. trade-offs) into implementing fuel management. After several simulation runs, I choose the size of each MU of 374 ha (925 acre), which allows a whole landscape to be burned under a severe weather condition only if each MU has fuel conditions that lead to very high or high spread rates. This size makes fuel management effective for mitigating the risk of fire loss and it will be an option which a land manager will consider. Therefore, optimal decisions will not always be extreme ones (corner solutions) such as harvest all MUs or not treating at all. This large area of ecologically homogenous management unit might not be a representative one for the region in which I am interested (eastern Oregon ponderosa pine-type dry forests). However, because my focus of this study is not to simulate fire behavior or growth as realistic as possible but to draw general insights into spatial allocation of fuel management, it is important to create a landscape which provides me with various spatial

[2] A two MUs structure, which is often used for analytical tractability, is not descriptive enough because only neighboring effects can be addressed

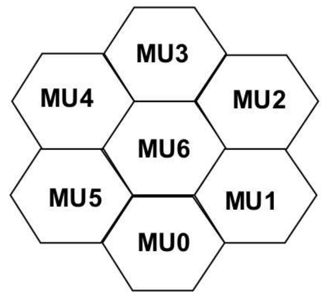


FIGURE 3.1: Hypothetical 7MUs landscape

management patterns as results rather than only extreme management strategies.

3.3.1. Decisions

A decision in each period is "which action should be taken in each MU" (a spatial allocation of actions) and it can be represented by a vector of actions. Each period has 10 year interval. I assume that prior to the current period, there was no fuel management. In the current period, a land manager chooses from four possible actions for each MU in the current period. The four possible actions are:

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

[3] Although an even-aged management is not often conducted in ponderosa pine-type forest, it is modeled because it allows me to compare the results with results from stand-level analysis in terms of the rotation age and to investigate the effects of spatial externalities on rotation ages.

In the 2nd period, only two actions, harvest and grow only, are available. Each MU will be managed for the financial optimal rotation age without the risk of fire forever after the 2nd period, which creates a terminal condition. Each decision is made at the beginning of each period. The current period's decision is made and applied prior to fire events in the current period.

3.3.2. States

In this model, two attributes, age class and fuel conditions, are used to represent the state of the system. Fuel conditions represent spread rates of fire. Fuel treatment slows down the spread rate of fire. Vegetation types represent the age class of trees growing in each MU. For example, zero to nine year old trees are classified into age class zero and 10 to 19 year old trees are classified into age class one and so on. This classification is commonly used in forest management.[4]

Tree growth in an MU is projected using the East Cascade Variant of the Forest Vegetation Simulator [43] . A tree list file which is representative of the eastern Oregon ponderosa pine forest was used for a growth simulation. Merchantable timber volume of each age class is shown in Table 3.1. Tree growth in each management unit is deterministic. Therefore, the only stochastic factor in this model is fire disturbance. Stand age class in an MU at t will transition to stand age class in that MU at $t+1$ in the following way:

${s_{age,t+1}}^i = {s_{age,t}}^i + 1$ no fire, not cut (i=1,2,...,7)

${s_{age,t+1}}^i = 0$ if fire or cut (i=1,2,...,7)

where ${s_{age,t}}^i$ is the stand age class in MU i at period t

[4] Forest plans in public land often define harvest rates by age class [42].

Each action in an MU changes the fuel condition of the MU depending on the initial fuel condition and vegetation type.

TABLE 3.1: Volume table

Age Class	Volume (mbf)
0	0
1	0
2	0
3	6.8
4	12
5	14.7
6	20.5
7	26
8	30.9
9	35.3
10	39.1

3.3.3. Parameters of Fire Model

Although, the framework developed here features spatial endogenous risk, the risk of fire damage is not totally endogenous because we cannot control, for example, ignition from lightning. Therefore, the probability of ignition is defined as an exogenous variable. The fire may ignite in any MU after the current period's decision is made. In the base case, each MU has a fixed ignition probability of 0.2. This ignition probability represents the probability of fire ignition over a decade[5].

Spatial fire patterns are partially determined by weather condition during the fire events because weather conditions define fire duration time[6]. For a given ignition location, fire fronts move depending on fuel conditions during the time frame specified by a fire duration time. Because we have no control over weather conditions, the frequency of different weather conditions during fire events is also defined as an exogenous random variable. In the base case, one of two weather conditions, mild and severe weather, is assumed to occur with probability of 0.6 and 0.4 respectively during a fire event. I assume that under mild weather conditions, fire duration is 48 hours [24]. Under severe weather conditions, fire duration time is 96 hours [24].

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

[5] 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.* [44] defined the probabilities of fire for different fire sizes. However, in this study, I used the average fire arrival rate to represent an ignition probability as studies by Amacher *et al.* [39] and Reed [5]. Reed used three different average fire arrival rates, 1%, 2% and 5%. According to Bork [45] the average fire arrival rate is ranging from around 2% to 6% for ponderosa pine forests in Oregon.

[6] Fuel moisture is also an important factor for fire growth [46]. Fuel moisture could vary over time depending on weather conditions [47][48]. However, in this study fuel moisture is assumed to be constant over time because defining fire durations for each weather condition creates weather-dependent fire growth patterns of my interest without a specific and detailed weather information which is necessary for modeling a dynamic fuel moisture content.

TABLE 3.2: Fuel conditions and spread rates

fuel conditons	descriptions	model	spread rate ($m\ min^{-1}$)
very high	age class < 2, no fuel treatment	Anderson, 1982	0.82
high	after clear cutting, age class 0	Anderson, 1982	0.66
medium	age >= 2, no fuel treatment	Anderson, 1982	0.35
low	fuel treatment age <2, or fire disturbance	Stephens, 1998	0.28
very low	fuel treatment with age >= 2	Stephens, 1998	0.18

seven possible ignition locations and two different weather conditions, a set of possible spatial fire patterns is derived from each spatial arrangement of fuel conditions.

In order to relate the spatial arrangement of fuel conditions to a set of possible spatial fire patterns, a fire simulation model is used. Fire simulation models project fire growth for a given spatial pattern of fuel conditions, weather conditions, and ignition points. Fire growth and behavior are modeled using Huygens' principle of wave propagation [12] , which is commonly used in fire behavior models such as FARSITE [11] and BEHAVE [23]. This technique simulates the growth of a fire front as a two-dimensional ellipse wave [49]. The dimensions of an elliptical wave are calculated using a spread rate that depends on fuel conditions. The five fuel conditions and spread rates I used in this study are shown in Table 3.2, along with reference to the fuel models (FM) from which they were adopted. I adopt three fuel models developed by Anderson [12]. These fuel models represent typical field situations for eastside forests and contain a profile of fuel characteristics (e.g. fuel particle surface-area-to-volume ratio) (see Appendix C). Because fuel models following various fuel treatments were not modeled by Anderson [12], I adopt custom fuel models developed by Stephens [50].

To simulate the fire front 360 points, which are arranged in circle, are expanded using the equations (see Appendix A) developed by Richards [49]. This set of equations predicts that how far each fire front point moves during the time frame which depends on weather conditions during fire event. Each fire front point is defined by x-y coordinates. The simulation model evaluates the fuel condition of each fire front point using x-y coordinates and uses the corresponding spread rate (see Appendix B) to expand that point.

The fire simulation model identifies whether an MU is burned or not for an initial distribution of fuels and age conditions for each possible ignition point and weather condition[7]. For simplicity, I define an MU is burned, if half of the area of the MU is burned[8]. To evaluate whether half of an area is burned or not, a grid of 127 grid points, which are distributed equally over an MU, are identified in each MU. Then, the fire simulation model evaluates whether more than half the number of grid points in each MU is burned or not by comparing the distance from the ignition point to each fire front point with the distance from the ignition point to each grid point closest to the fire front point. If the distance between the ignition point and a grid point is shorter than the distance between the ignition point and a fire front point, then the grid point is identified as burned. A counter in the program counts the number of grid points burned. For a given landscape, a weather condition, and ignition point, the simulation model is deterministic, so the probability of spread from MUi to MUj, γ_{ij} is a binary variable equal to 1 if unit j burns and

[7] The output from a single fire simulation run represents the 10-year's worth of fires. Annual ignition probability is adjusted to a decade average ignition probability. It could be possible to run a fire simulation for every year for 10 years to represent spatial fire patterns for a decade, however precisely projecting spatial fire pattern is not the focus of this study. A single fire simulation run provides a wide range of possible fire patterns and their probabilities for the purpose of this study, which is to analyze a land manager's behavior for a given set of possible fire patterns. Representing a period with a 10 year interval in between periods also assumes that the fuel treatment conducted will be effective for reducing fire hazard for 10 years. Several studies show that this assumption is reasonable [51] [52].

[8] Fire does not necessarily kill trees. Tree death by fire is a function of crown scorch height and tree diameter [53]. Under conditions where litter and understory fuel build up due to longer fire-return intervals, crown fires with high intensity can occur in ponderosa pine type forests [53] [54]. Because I am interested in cases where fires destroy timber which causes financial loss for landowners, I only consider cases where fires initiate crown fires, damage trees and results in total loss of timber value.

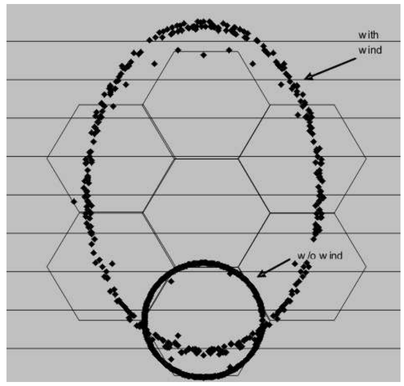


FIGURE 3.2: Output from fire simulation model showing fire growth

0 if unit j does not burn.

With five fuel condition classes and seven MUs, there are 16,943 unique spatial configurations of fuel conditions for the landscape after a decision has been applied but before a fire event has occurred. A fire is simulated and a spatial configuration of fire occurrence (a vector of γ_{ij}'s) is generated for each of fuel condition configuration, for each weather condition, and for each ignition point - 16,943*7*2 = 237,202 simulations. The simulation model was programmed in C and took 28 hours on the main machine with dual 3.06 GHz CPU and 2 GB of RAM.

Figure 3.2 shows an example of the output from the fire spread simulation used for this study.

3.3.4. Economic Parameters

The specific economic parameters used in the base case (Table 3.3) are within a range of realistic values and reflects the relative values, which makes the appropriate decision less obvious. For example, although fuel treatment costs may vary from around \$50/acre to over \$1,000/acre depending on stand (or MU) types [55], the value chosen for the base case relative to the other parameter values allows a land manager to choose

TABLE 3.3: Economic parameters for the base case

Discount Rate	4%
Stumpage Price	$500/mbf
Fuel Treatment Cost	$200/acre
Regeneration Cost	$200/acre

various investment levels of fuel treatments depending on spatial configurations of fuel conditions. In the base case a discount rate of 4 % is assumed for calculate of net present value. The base case uses stumpage price of $500/acre, regeneration cost of $200/acre and fuel treatment cost of $200/acre. In chapter 5, I evaluate various economic environments around the base values.

I assume that stumpage price does not vary due to a fire disturbance. A land manager faces horizontal demand function for timber. In the base case, the land manager is assumed to be a price-taker. This would be true if changes in timber supply from this landscape are too small to affect stumpage price. Ending values are calculated for each MU assuming that it will be managed for the financial optimal rotation age without the risk of fire forever after the 2nd period, which creates a terminal condition as I focus on the first period's decision.

3.4. Solution Algorithm

Backwards induction is used to solve this dynamic problem numerically. The algorithm first identifies the optimal decision in the 2nd period for each state ${S_n}^{t+1}$ by complete enumeration. The optimal decision is the one that generates the highest value at the beginning of the 2nd period, $V(S_n{}^{t+1})$. The optimal decision for the current period depends on the expected value of the best value in the 2nd period:

$$E[V(S_n^{t+1})] = \sum_{n=1}^{N} P(S_n^{t+1} \mid S_m^t, D_k^t) \cdot V(S_n^{t+1}) \tag{3.3}$$

It is computed using the transition probability matrix generated through fire simulation runs. Again, complete enumeration is used to find the current period's optimal decision given the optimal 2nd period's decision.

The algorithm was written in the C and C++ language (see Appendix D). The main PC used for computation has dual 3.06 GHz CPU and 2 GB of RAM. Solution run-times were approximately 80 min on this main PC. In addition to the main machine, 15 PCs with a 3.4 GHz CPU and 2GB of RAM in a computer lab and two PowerMac G5s with dual 2 GHz CPU and 1GB of RAM were used for sensitivity analyses and fire simulation runs.

4. RESULTS

In this section, I show the numerical solutions for spatial forest management problems under the risk of fire damage. Before showing these solutions, I will characterize the solutions generated from my framework and briefly discuss the concept of the important trade-offs involved in fuel management decisions. The following discussion of trade-offs builds a foundation for the arguments in this study.

Several issues are discussed in this section using numerical solutions. First, a general strategy is developed for implementing cost effective spatial fuel management efforts. Then, the concept of spatial externality is discussed. This concept is important for spatial management problems. I also compare my optimal decisions to "rule of thumb" strategies and strategies generated from previous research. Lastly, I compare the decisions generated by two different decision makers, who treat forthcoming information differently. The analyses presented here demonstrate that ignoring the spatial aspects of fire patterns, fuel conditions, and actions taken leads to suboptimal decisions.

4.1. Characterization of Results

My framework generates the current period's optimal spatial management effort allocation by taking into account the possible values obtained in the 2nd period given a current period decision. Fire events may occur between the current period and the 2nd period. Unlike other studies, the optimal decision generated from the framework is not the optimal path of actions over multiple periods. Because the framework searches for the optimal decision out of all possible decisions, each of which yields numerous possible fire patterns, extension to a three period or longer period model increases computational efforts (computational time and memory) significantly and problems become easily untractable.

In this study I do not assume a single homogeneous landscape (in terms of fuel and age class conditions). The framework searches the optimal decision for many possible initial spatial configurations of fuel conditions which allow me to derive general insight into implementing spatial forest management efforts and to demonstrate my analyses for a range of ecological characteristics.

To construct a set of possible initial spatial configurations, I assume that a land manager has not conducted any fuel treatments and has not conducted harvest recently. This assumption is made because, so far, too little area has been treated due to a limited budget especially in public lands. Then, I need to consider only combinations of two fuel types (very high spread rate and medium spread rate) as initial conditions. Furthermore, I assume that all MUs with medium spread rates have an age class of three (except in section 4.6). Because without the risk of fire, harvesting at age class 4 is financially optimal, MUs of age class 4 will always be harvested immediately, which makes a land manager's decision of spatial allocation of harvest and fuel treatment less interesting. Because wind directions and slopes are not considered in this chapter (they are included in the model in chapter 5), I am able to represent any mirror images with a single spatial arrangement.

4.2. Concept of Trade-Offs

The framework explicitly address three important tradeoffs for evaluating cost effective spatial allocation of fuel management efforts - fuel treatments and harvest - as described in chapter 3. Decisions involve trade-offs across time. Because newly regenerated stands have a higher fire spread rate than mature stands, harvest increases fire risk. As a result, fire risk affects optimal harvest age. Because fuel treatment is costly, a land manager will accept more risk as the cost of fuel treatment increases. If a recently harvested MU is left untreated, an ignition from this MU will damage this MU itself, spread to adjacent MUs and increase the risk of value loss not only in this MU but also in adjacent MUs. Therefore, leaving these MUs untreated can reduce the expected NPV significantly. If a land manager wants to, he or she may accept a certain level of risk

4.3. Spatial Pattern, Spatial Externalities and Spatially Explicit Trade-offs

For both private and public agencies, spatially allocating fuel management efforts - fuel treatments and harvest - in a cost effective manner becomes an important issue because many areas must be treated immediately within a limited budget. By solving management problems for a number of landscapes, I draw insight into implementing efficient spatial fuel management efforts.

I investigate the effects of spatial interactions across MUs during forest fire - in particular a spatial externality - on efficient allocation of fuel management efforts, which are intended to mitigate the risk of wildfire damage. These spatial externalities are captured in a spatial endogenous risk framework. I focus here on the impact of two types of spatial externalities. First, if an MU with a very high spread rate is left untreated, and if adjacent MUs are not treated, fire ignition from this MU will spread into adjacent MUs. The management decision on one MU alters the fire risk facing other MUs. Second, harvesting an MU without fuel treatment increases the spread rate of fire and, therefore, increases fire risk on neighboring MUs. As a result of these spatial externalities, land managers face spatial trade-offs which affect the optimal spatial pattern of fuel treatment and the optimal timing of harvest.

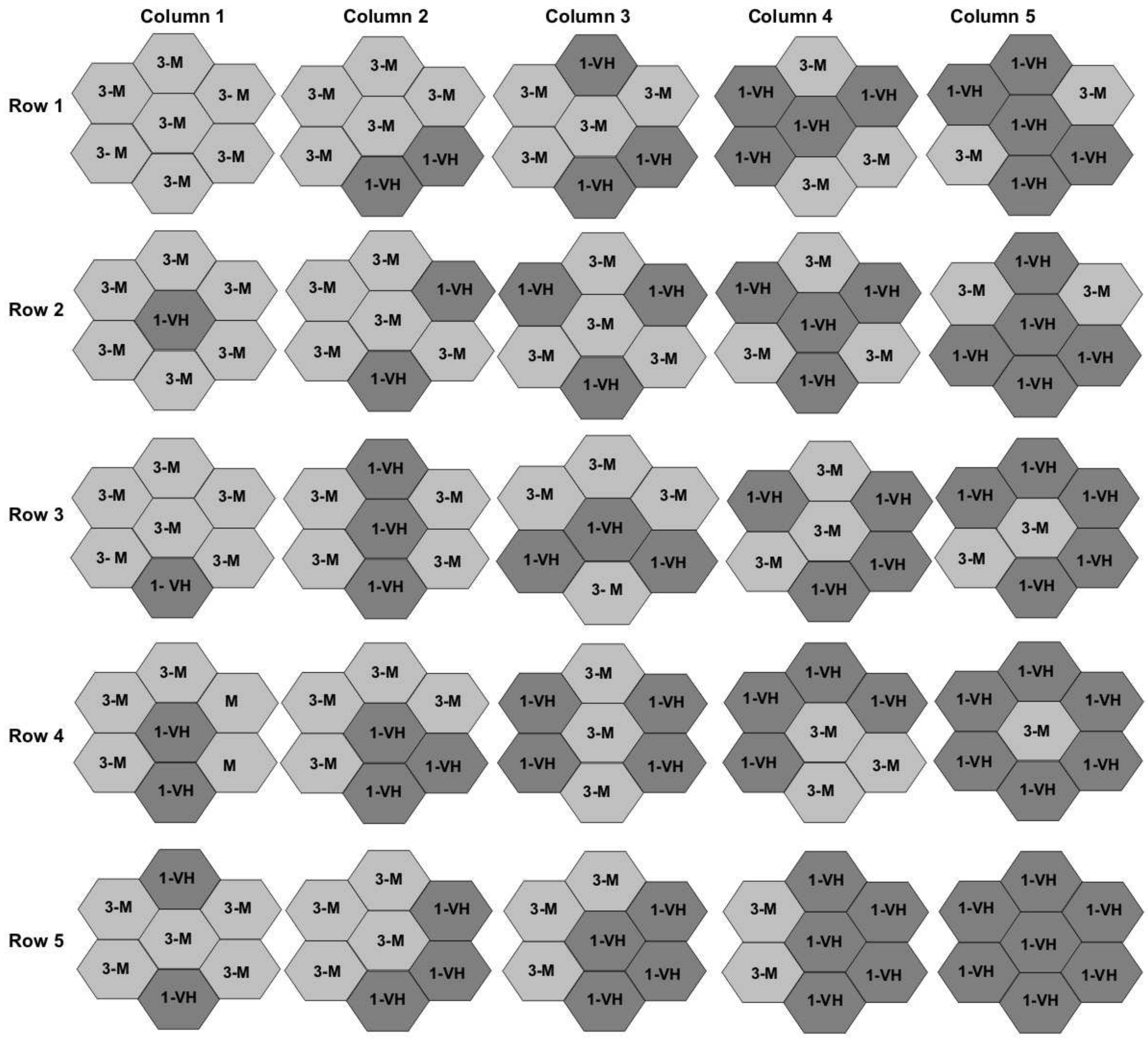
To illustrate this issue, I analyze the optimal spatial arrangement of fuel conditions for 25 different initial spatial configurations (Figure 4.1). An SDP problem is solved for each initial spatial configuration. The optimal decision for each spatial configuration is shown in Figure 4.2. MUs labeled "fuel" are the MUs where a land manager assigns fuel treatment. MUs labeled "grow" are the MUs where a land manager does nothing. MUs labeled "cut" are the MUs where a land manager conducts harvest. MUs labeled "cut&fuel" are the MUs where a land manager harvests and assigns fuel treatment. The spatial arrangement of fuel condition that results from the current period's optimal decision for each initial spatial configuration is shown in Figure 4.3. MUs labeled "3-M" have a medium spread rate and are age class three ("3" represents an age class and "M" represents a spread rate). MUs labeled "1-VH" have a very high spread rate and are age class one. MUs labeled "1-L" have a high spread rate and are age class one. MUs labeled "1-VH" have a very high spread and age class one. MUs labeled "3-VL" have a very low spread rate and age class three. MUs labeled "1-L" have a low spread rate and age class one.

A land manager spatially assigns fuel treatments so that MUs with high spread rates ("1-VH") are separated from each other in an optimal landscape (Figure 4.3). Separating MUs with high spread rates reduces the risk of a significant loss of value (loss of value in multiple MUs) because this strategy slows downs the spread of fire when fire fronts move into treated MUs. When an ignition leads to fire damage in only one MU, a land manager often obtains a higher expected NPV than that obtained in the case where each ignition leads to fire damage in multiple MUs.

A land manger always treats the center MU if it has a very high spread rate (labeled "VH") (Figure 4.1 and Figure 4.2). If the very high spread rate center MU is not treated, fire ignition from this MU spreads all over the landscape and causes a significant loss of value. When the center MU has a moderate spread rate (age class 3), deciding whether or not to treat this MU depends on spatial configurations. For example, in landscape Figure 4.2 row 5 column 1, a land manager treats valuable (age class 3) MUs, including the center MU. However, in landscape Figure 4.2 row 4 column 5, a land manager treats all MUs with very high spread rates, but not the center MU.

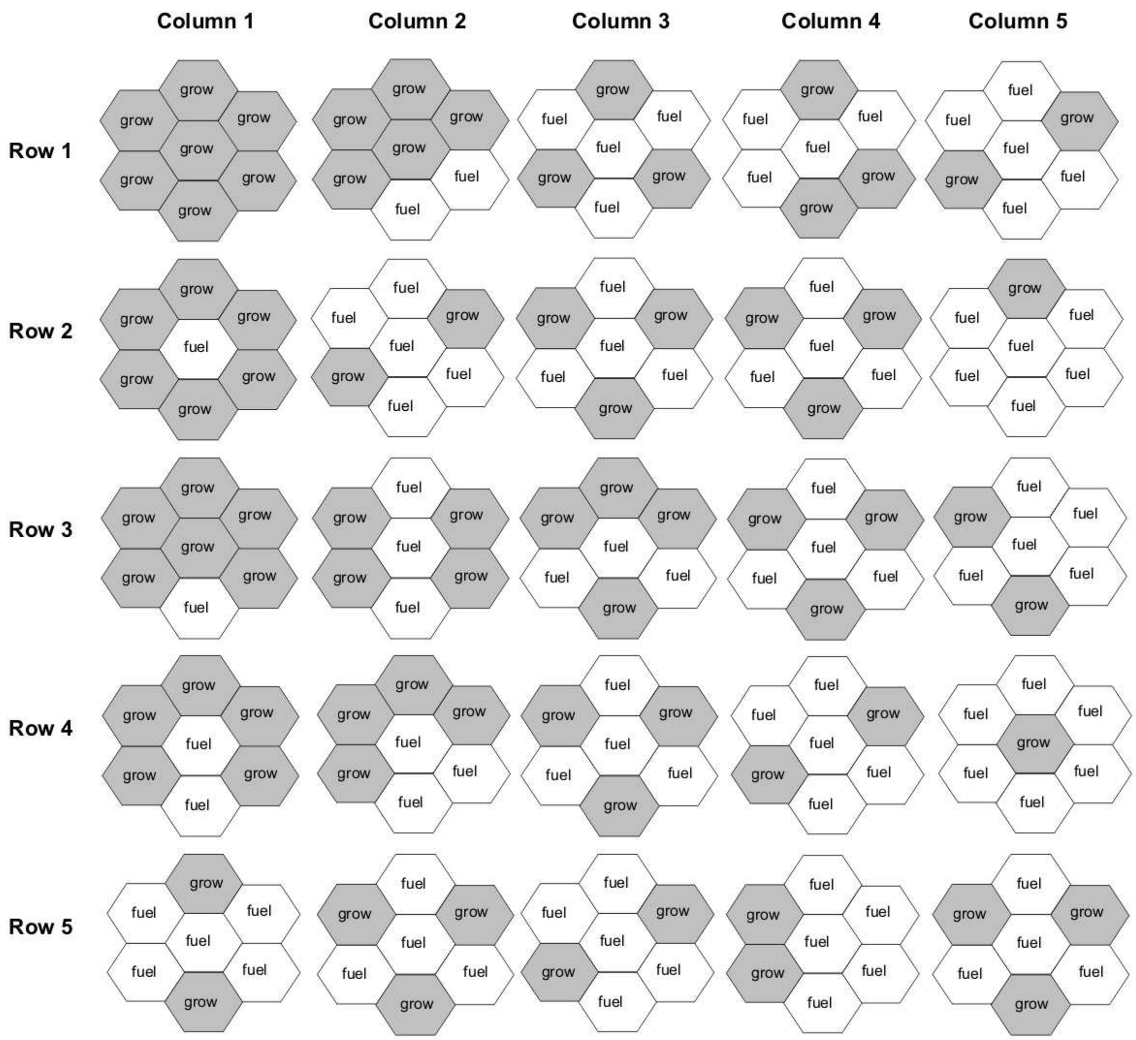
A land manager faces trade-offs between protection of on-site values and prevention of the spread of fire. Although a land manager has more incentive to treat valuable MUs, sometimes it is optimal to leave these valuable MUs untreated and to treat less valuable MUs with high spread rates (Figure 4.2). In this case, treating these less valuable MUs reduces the risk of value loss by fire damage in multiple MUs. Depending on initial spatial configurations a land manager prioritizes which MUs are most important to treat.

For landscapes with some MUs with very high spread rates, the optimal landscapes following management fall into two categories: a landscape in which all MUs with very high spread rates (VH) are treated or a landscape where all MUs with very high spread rates are surrounded by treated MUs after the optimal decision is conducted (Figure 4.3). (If MUs with VH are treated, their fuel condition changes to a low spread rate (L). If MUs with M are treated, their fuel conditions change to a very low spread rate (VL).) These optimal landscape results demonstrate a strategy of separating MUs with VH. The results demonstrate that a land manager fully take into account the cost of the spatial externality either by treating MUs with VH or by treating their adjacent MUs depending on initial spatial configurations of fuel conditions (Figure 4.1, Figure 4.2, and, Figure 4.3).



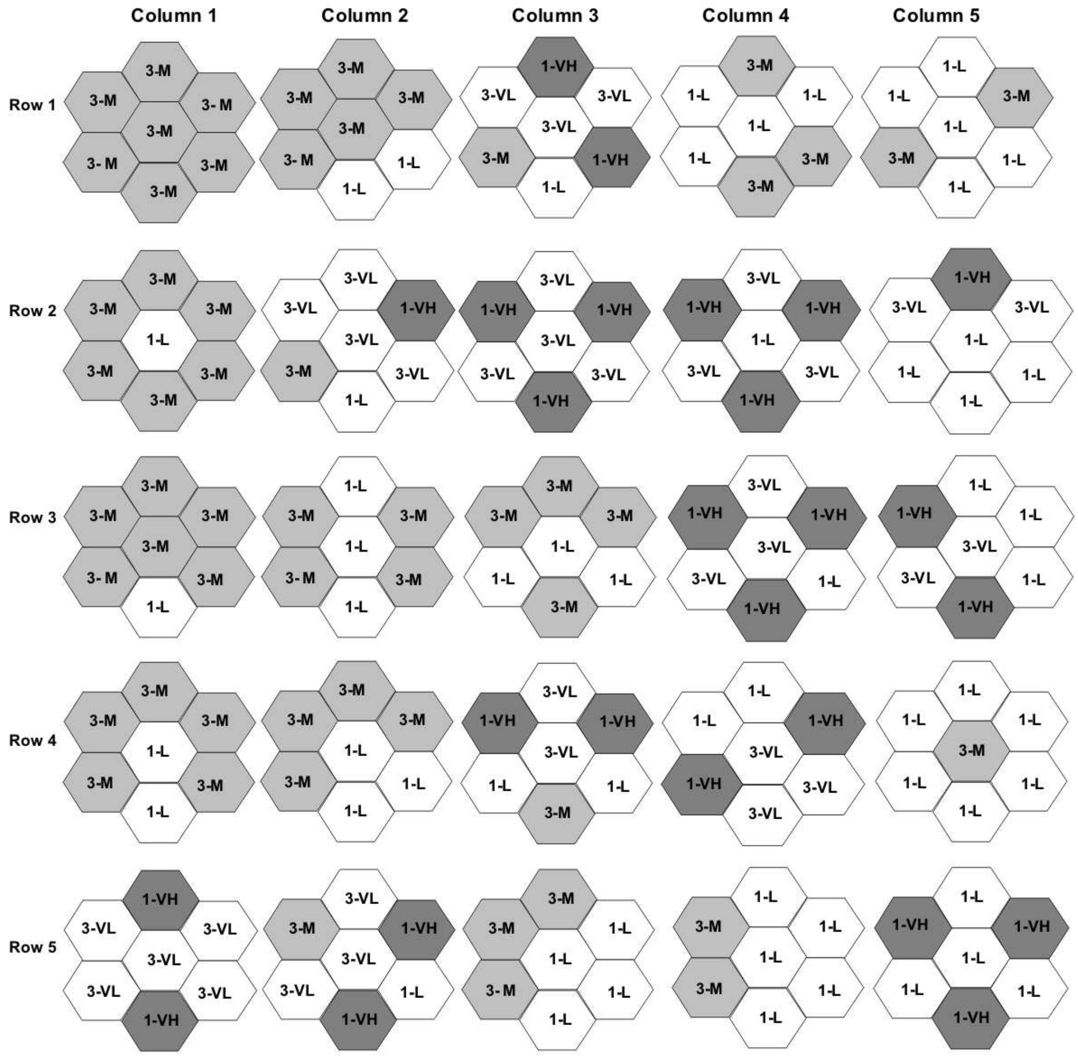
Fuel Condition Class				
VL = Very Low	L = Low	M = Medium	H = High	VH = Very High

FIGURE 4.1: Spatial configuration of age class and fuel condition class for initial landscapes (labeled "age class - fuel condition")



Actions			
cut = harvest	cut&fuel = harvest and fuel treatment	fuel = fuel treatment	grow = grow only

FIGURE 4.2: Spatial configuration of optimal decisions (labeled "action")



Fuel Condition Class				
VL = Very Low	L = Low	M = Medium	H = High	VH = Very High

FIGURE 4.3: Spatial configuration of age class and fuel condition class after optimal decision is applied (labeled "age class - fuel condition")

In this model, when fire risk is ignored, it is financially optimal to harvest when an MU reaches age class 4. In an aspatial model, fire risk shortens rotation because, as Reed [5] demonstrated, the probability that a stand will burn acts as a risk premium on the discount rate. But in a spatial model, because young stands have a higher fire spread rate, harvesting a stand increases fire risk in adjacent stands, which causes land managers to postpone harvest in order to reduce risk in adjacent stands.

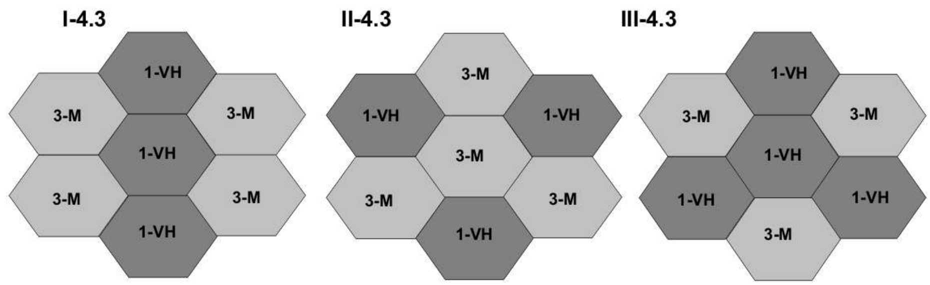
I define a threshold risk level as the level of fire risk (i.e. probability that an MU will burn) that induces a land manager to change the age class harvested from that of the financial optimum without risk.

To demonstrate the existence of the spatial harvest externality, I first compute the threshold risk level for a single MU without spatial interdependency. It is 0.068. If probability that an MU will burn exceeds that level, the MU will be harvested at age class 3 rather than age class 4.

I then solve the spatial model for three initial landscapes (Figure 4.4). I add a constraint to the model limiting the number of MUs that can be treated to one. This budget constraint ensures that the risk in each MU cannot be reduced to a low level by treating several MUs and forces a land manager to face trade-offs between harvesting and fuel treatment.

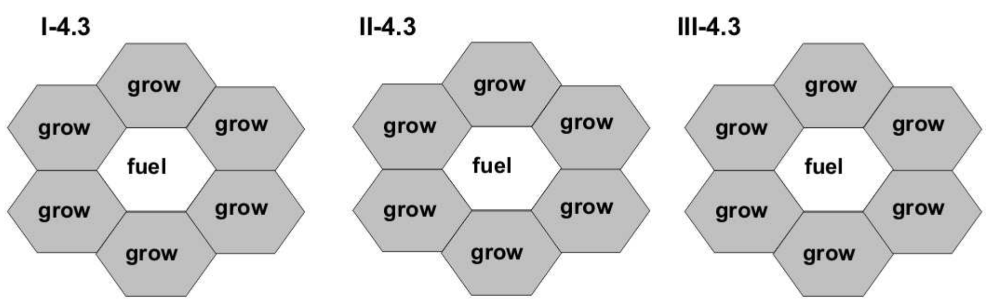
In all three solutions, the center MU is chosen for treatment (Figure 4.5). The near-mature (age class 3) units in the outer ring are not harvested even though the resulting fire risk levels (0.0734, 0.0944, 0.1153 for landscapes I-4.3,II-4.3 and III-4.3respectively) exceed the risk threshold in the aspatial model of 0.0688.

These results demonstrate that when a spatial externality is considered, a land manager will accept a higher risk than the threshold risk from an aspatial model. Harvesting an MU without fuel treatment will increase the spread of fire in that MU, which will



Fuel Condition Class				
VL = Very Low	L = Low	M = Medium	H = High	VH = Very High

FIGURE 4.4: Spatial configuration of age class and fuel condition class for initial landscapes (labeled "age class - fuel condition")



Actions			
cut = harvest	cut&fuel = harvest and fuel treatment	fuel = fuel treatment	grow = grow only

FIGURE 4.5: Spatial configuration of optimal decisions (labeled "action")

increase the risk of fire damage not only in that MU but also in adjacent MUs.

This concept of a spatial externality arises because fire grows and spreads in a spatially explicit way from one MU to another. Without a spatially explicit model, such a spatial externality cannot be addressed. Explicitly addressing the spatial externality is important because it will determine the action chosen for other MUs. Failing to consider the spatial externality leads to an inefficient solution.

4.4. Comparison with "Rule of Thumb" Strategies

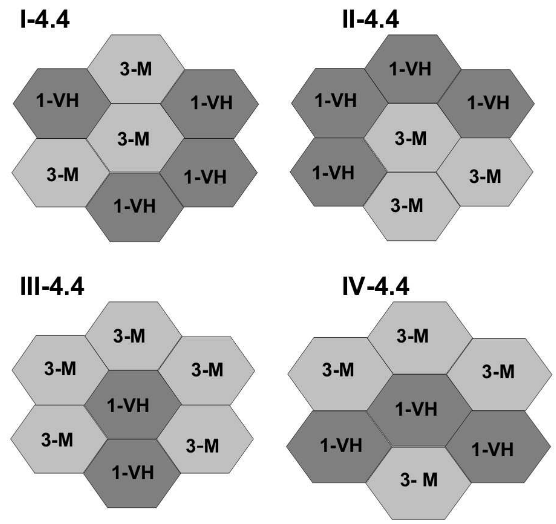
Implementing a full spatial model can be costly or require extensive information. Therefore it is necessary to identify the situations where the aspatial model is a good approximation for a full spatial model versus situations where the aspatial model deviates from a full spatial model. In this section, this identification is done by comparing management plans with spatial components to management plans without spatial components. "Rule of thumb" strategies such as protecting all valuable MUs ignore spatial dimensions. When implementing a full spatial model is too costly or requires extensive information, a land manager relies on "rule of thumb" strategies. I compare the optimal decision, which takes into account spatial interactions and spatial externality, with "rule of thumb" strategies to find out: 1) what the differences are between the optimal and second-best solutions 2) in which situations will second best solutions be close to optimal, and in which situations will second best solutions not work. The decisions made by using "rule of thumb" strategies will be second-best solutions. In order to identify situations where second best solutions will be optimal or close to optimal, four different initial spatial configurations (I-4.4, II-4.4, III-4.4 and IV-4.4) are analyzed (Figure 4.6). Four different "rule of thumb" strategies are developed for comparison:

- Treating (protecting) all MUs with very high spread rates - a strategy for a land manager who is concerned about the spread of fire.
- Treating all valuable MUs - a strategy for a land manager who is concerned about his or her valuable MUs (In this framework, a land manger tries to protect all MUs with age class 3 because these MUs have higher values of merchantable timber)
- Treating all MUs regardless of fuel conditions and fuel treatment costs - a strategy for a land manager who wants to minimize the risk of value loss at any cost.
- Not-protecting any regardless of fuel conditions and fuel treatment costs - a strategy for a land manager who does not care about the risk of fire damage.

A land manager assigns fuel treatment to MU1, MU3, MU5 and MU6 in landscape I-4.4 (Figure 4.7). All valuable MUs and one of the MUs with a very high spread rate are treated according to the optimal decision.

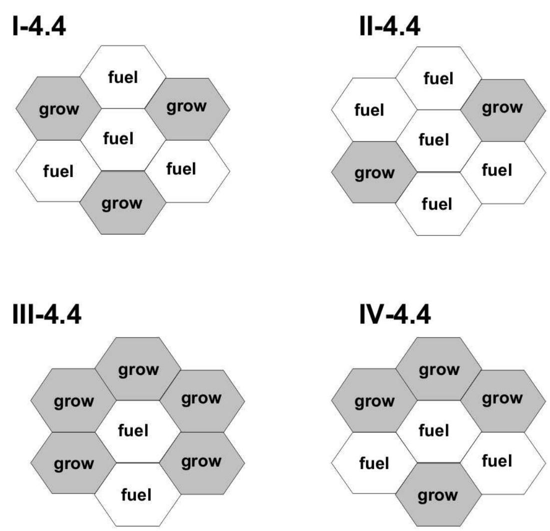
MU1 that has a very high spread rate is treated because if this MU is left untreated, then the landscape contains three connected MUs with very high spread rates, which leads to value loss in multiple MUs. By treating MU1, MUs with very high spread rates are separated from each other.

In landscape I-4.4, the "rule of thumb" strategy of treating all valuable MUs (Figure 4.8) leaves three connected MUs with high spread rates untreated and is sub-optimal because contiguity of MUs with very high spread rates leads to a significant value loss of multiple MUs (Table 4.1 figures in this table is in $/acre). The "rule of thumb" strategy of treating all MUs with very high spread rates (Figure 4.9) yields a lower objective value than the optimal decision yields (Table 4.1) even though this strategy



Fuel Condition Class				
VL = Very Low	L = Low	M = Medium	H = High	VH = Very High

FIGURE 4.6: Spatial configuration of age class and fuel condition class for initial landscapes (labeled "age class - fuel condition")



Actions			
cut = harvest	cut&fuel = harvest and fuel treatment	fuel = fuel treatment	grow = grow only

FIGURE 4.7: Spatial configuration of optimal decisions (labeled "action")

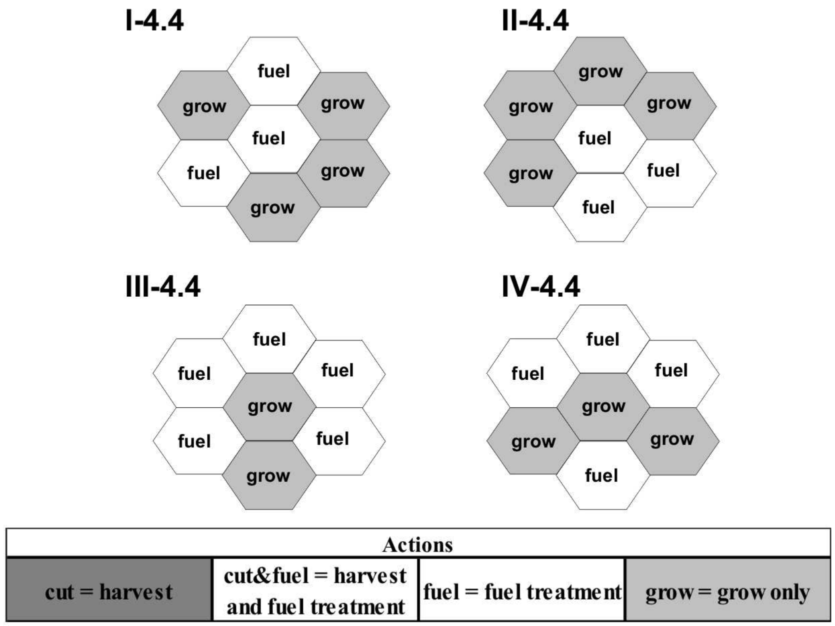


FIGURE 4.8: Spatial configuration of "Rule of thumb" strategy - protecting all valuable MUs (labeled "action")

TABLE 4.1: Comparison of NPV ($/acre) for landscape I-4.4

		Rule of thumb strategies			
	Optimal decision	Protect all valuable MUs	Protect all MUs with high spread rates	Protect all MUs	No protection
Current period	-800	-600	-800	-1,400	0
Future period	22,203	21,205	21,953.54	22,436.85	19,644.63
Total	21,403.05	20,604.94	21,153.54	21,036.85	19,644.63

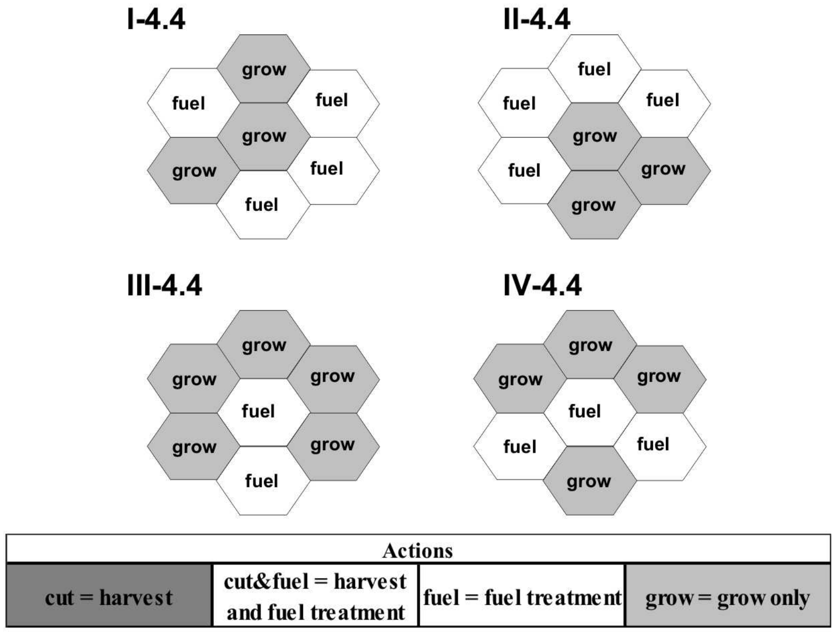


FIGURE 4.9: Spatial configuration of "Rule of thumb" strategy - protecting all MUs with very high spread rates (labeled "action")

requires the same number of MUs to be treated as the optimal decision. Because none of the valuable MUs are treated with this "rule of thumb" strategy, the value obtained from protection become smaller than the value obtained from the optimal decision. If all MUs are treated, then this strategy will yield the highest expected value in the 2nd period because the risk of fire loss is minimized (Table 4.1). However, the cost in the current period is also the highest with this strategy. Overall, the objective value of this strategy is lower than the optimal value (Table 4.1). Therefore, from the perspective of cost-effectiveness of fuel management, the landscape is overprotected with this strategy. On the other hand, if no MUs are treated, then this strategy yields the lowest expected value among the four strategies in the 2nd period (Table 4.1). With this strategy, there is no cost in the current period. This result indicates that future objective values can be significantly increased by protecting some MUs.

A land manager assigns fuel treatment to MU0, MU1, MU3, MU4 and MU6 in landscape II-4.4 (Figure 4.7). According the optimal decision two of MUs with very high spread rates (MU3 and MU4) are protected in a way that these high spread rate's MUs are separated from each other (Figure 4.7). Also all valuable MUs are protected according to the optimal decision (Figure 4.7).

In landscape II-4.4 the "rule of thumb" strategy of treating all valuable MUs (Figure 4.8) leaves four MUs with very high spread rates untreated. Therefore, the risk of value loss in multiple MUs becomes high and the expected NPV decreases significantly (Table 4.2). The "rule of thumb" strategy of treating all MUs with very high spread rates (Figure 4.9) yields a lower objective value than the optimal decision yields because none of the valuable MUs are treated with this "rule of thumb" strategy (Table 4.2). If all MUs are treated, then this strategy yields the highest expected value in the 2nd period because the risk of fire loss is minimized (Table 4.2). However, the cost in the current period is also the highest with this strategy. Overall, the objective value of this strategy is lower than the optimal value (Table 4.2). Therefore, from the perspective of cost-effectiveness of fuel management, the landscape is overprotected with this strategy. On the other hand, if no MUs are treated, then this strategy yields the lowest expected value among the four strategies in the 2nd period (Table 4.2). With this strategy, there is no cost in the current period. This result indicates that future objective values can be significantly increased by protecting some MUs.

A land manager assigns fuel treatment to MU0 and MU6 in landscape III-4.4 and assigns fuel treatment to MU1, MU5 and MU6 in landscape IV-4.4 (Figure 4.7). In both landscapes, all MUs with a very high spread rate are treated according to the optimal decision. Therefore, the "rule of thumb strategy" of protecting all MUs with very high

TABLE 4.2: Comparison of NPV ($/acre) for landscape II-4.4

		Rule of thumb strategies			
	Optimal decision	Protect all valuable MUs	Protect all MUs with high spread rates	Protect all MUs	No protection
Current period	-1,000	-600	-800	-1,400	0
Future period	22,203	20,619	21,953.54	22,436.85	19,844.07
Total	21,203.06	20,019.00	21,153.54	21,036.85	19,844.07

spread rates is optimal in these landscapes. The "rule of thumb" strategy is optimal because by treating only two or three MUs with very high spread rates the optimally managed landscape contains no MUs with very high spread rates. On the other hand, the "rule of thumb strategy", protecting all valuable MUs (Figure 4.8), is not optimal because two or three connected MUs with very high spread rates are left untreated. These untreated MUs cause multiple MUs to be burned if fire ignites from one of these, which lead to large financial loss. If all MUs are treated, then this strategy yields the highest expected value in the 2nd period because the risk of fire loss is minimized. However, the cost in the current period is also the highest with this strategy. Overall, the objective value of this strategy is lower than the optimal value (Table 4.3 and Table 4.4). Therefore, from the perspective of cost-effectiveness of fuel management, the landscape is overprotected with this strategy. On the other hand, if no MUs are treated, and then this strategy yields the lowest expected value among the four strategies in the 2nd period (Table 4.3 and Table 4.4). With this strategy, there is no cost in the current period. This result indicates that future objective values can be significantly increased by protecting some MUs.

The results show that "rule of thumb strategies" such as protection of all valuable MUs or protection of all MUs with high spread rates might not be optimal when 1) a "rule

TABLE 4.3: Comparison of NPV ($/acre) for landscape III-4.4

		Rule of thumb strategies			
	Optimal decision	Protect all valuable MUs	Protect all MUs with high spread rates	Protect all MUs	No protection
Current period	-400	-1,000	-400	-1,400	0
Future period	26,907	26,498	26,907	27,647.29	24,397.10
Total	26,506.75	25,497.63	26,506.75	26,247.29	24,397.10

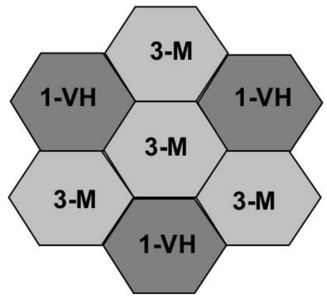
TABLE 4.4: Comparison of NPV ($/acre) for landscape IV-4.4

		Rule of thumb strategies			
	Optimal decision	Protect all valuable MUs	Protect all MUs with high spread rates	Protect all MUs	No protection
Current period	-600	-800	-600	-1,400	0
Future period	24,430	23,165	24,430	25,050.38	21,973.30
Total	23,830.15	22,364.90	23,830.15	23,650.38	21,973.30

of thumb" strategy leaves connected multiple MUs of high spread rates untreated and 2) failing to treat valuable MUs lowers the expected NPV. These analyses demonstrate when a decision maker ignores spatial aspects of decisions, he or she conducts too much (little) protection of the landscape or spatially misallocate fuel treatments.

4.5. Comparison with Strategies for "Target" Fire

Some researchers have developed a framework to find the optimal decision for a particular fire pattern that is anticipated. They use a particular fire size and shape, which



Fuel Condition Class				
VL = Very Low	L = Low	M = Medium	H = High	VH = Very High

FIGURE 4.10: Spatial configuration of age class and fuel condition class for initial landscape (labeled "age class - fuel condition")

is called a "target fire", and find the optimal decision when the "target fire" is predicted to occur. However, in this study, a particular "target fire" is not assumed. The exact spatial pattern of the fire is unknown. The question is "what is the cost of assuming a "target fire" occurs when a "target fire" is just one of many possible fires?"

Two target fires are used for comparison. One target fire is developed by assuming an ignition from MU0 under severe weather conditions (hereafter denoted as TARGET-MU0). This assumption creates a single fire pattern for each decision. The other target fire is developed by assuming an ignition from MU6 under severe weather conditions (hereafter denoted as TARGET-MU6). The base case does not assume a particular target fire (i.e. random ignition locations and weather conditions). Figure 4.10 depicts the initial spatial configuration used to illustrate this issue.

A land manager assigns fuel treatments to four MUs (MU1, MU3, MU5 and MU6) on the landscape (Figure 4.11) for the base case and assigns fuel treatment only to MU0 for TARGET-MU0 (Figure 4.11) and assigns fuel treatment to four MUs (MU0,MU2, MU4, and MU6) for TARGET-MU6 (Figure 4.11).

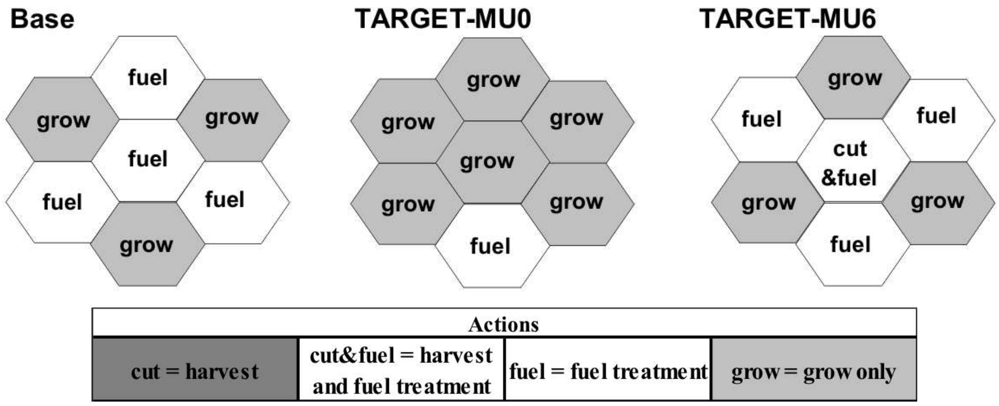


FIGURE 4.11: Spatial configuration of optimal decisions for each case (labeled "action")

When a "target" fire is unknown, a land manger treats four MUs to mitigate the risk of value loss resulting from many possible fire patterns. For TARGET-MU0, a land manger treats only MU0 because fire ignition in MU0, which is surrounded by MUs with slower spread rates (i.e. medium spread rate), is a certain event. For TARGET-MU6, because fire that ignites from MU6 spreads to adjacent MUs, fuel treatment is conducted in MU6, after it is harvested. MU0, MU2 and MU4 are treated because these MUs have very high spread rates, which, if not treated, will allow fire to damage these and other MUs.

The base case optimal decision costs more in the current period ($800/acre) than the optimal decision for TARGET-MU0 (Table 4.5). However, for the base case the expected NPV obtained in the 2nd period is $1950/acre more than that obtained from the optimal decision for TARGET-MU0 (Table 4.5). A land manager obtains the positive revenue in the current period for TARGET-MU6 and the revenue in the current period is the highest among three cases (Table 4.5). However, for TARGET-MU6 the expected NPV obtained in the 2nd period is $3,800/acre less than that obtained from the optimal decision for the base case (Table 4.5).

For TARGET-MU0, a land manager treats only MU0 in order to mitigate the risk of value loss in the MUs and pays the cost for a single treatment because fire ignition from MU0 is a certain event and MU0 is surrounded by MUs with slower spread rates (i.e. medium spread rates). However, ignoring other possible fire patterns and treating only MU0 increase the risk of value loss in MUs and significantly lower the expected NPV obtained in the 2nd period (Table 4.5). For TARGET-MU6, although a land manager treats the same number of MUs as the base case, harvesting MU6 before it reaches a financially optimal rotation age lowers the expected NPV obtained in the 2nd period (harvesting MU6 during the current period makes the current period's revenue highest among three cases). A land manager harvests MU6 when it is near maturity because a loss of value in MU6 is a certain event during the current period for TARGET-MU6.

If only a particular fire is considered as TARGET-MU0 or TARGET-MU6, the decision is made under certainty. The decision made for the target fire scenario is the best decision in a particular state (i.e. a particular fire pattern). This decision is, in fact, a 2nd stage decision, where the only tradeoffs considered are between costs and benefits not between costs, benefits and risks of value loss.

On the other hand in the base case, the SDP model evaluates the tradeoff between costs of fuel treatments, revenues from harvest, and the risk of value loss and yields a higher total value. Because my framework deals with a wider solution space by considering other fire patterns, decisions involve an evaluation of many scenarios (i.e. fire patterns). When the strategy generated for a "target" fire does not mitigate the risk of value loss in MUs for other possible fire patterns, then it yields the lower objective value and becomes sub-optimal. The framework generates efficient solutions in cases where it is unknown which fire pattern will occur.

TABLE 4.5: Comparison of NPV ($/acre) for target fires and an unknown fire

	Target Fire		All Possible Fires
	TARGET-MU0	TARGET-MU6	Base case
current period	-200.00	2,400.00	-800
future period	23,101.34	21,305.36	25,050.38
total	22,901.34	23,705.36	24,250.38

4.6. "Myopic" and "Foresighted" Land Managers

Two different land managers, who treat forthcoming information differently, will often make different decisions. In particular, a land manager who does not value and consider the role of forthcoming information in the current period's decision often makes suboptimal decisions [28].

Two different equations are used to represent the optimization problems of two different types of land managers. A "foresighted" land manager is the one who considers forthcoming information in the current period decision. A "foresighted" land manager's problem is formulated as a closed loop system (Eq.[4.1]). A "myopic" land manager is the one who does not consider forthcoming information in the current decision. A "myopic" land manager's problem is formulated as an open loop system (Eq.[4.2]).

$$V(S_m^t) = \max_{D_k^t}\{v(S_m^t, D_k^t) + \delta \cdot \sum_{n=1}^{N} P(S_n^{t+1} \mid S_m^t, D_k^t) \cdot \max_{D_k^{t+1}}\{v(S_n^{t+1}, D_k^{t+1})\}\} \tag{4.1}$$

$$V(S_m^t) = \max_{D_k^t}\{v(S_m^t, D_k^t) + \delta \cdot \max_{D_k^{t+1}}\{\sum_{n=1}^{N} P(S_n^{t+1} \mid S_m^t, D_k^t) \cdot v(S_n^{t+1}, D_k^{t+1})\}\} \tag{4.2}$$

Differences in optimal decisions arise when forthcoming information is valuable, or the expected value of information is positive, which is represented by E[max($\cdot$)] > max

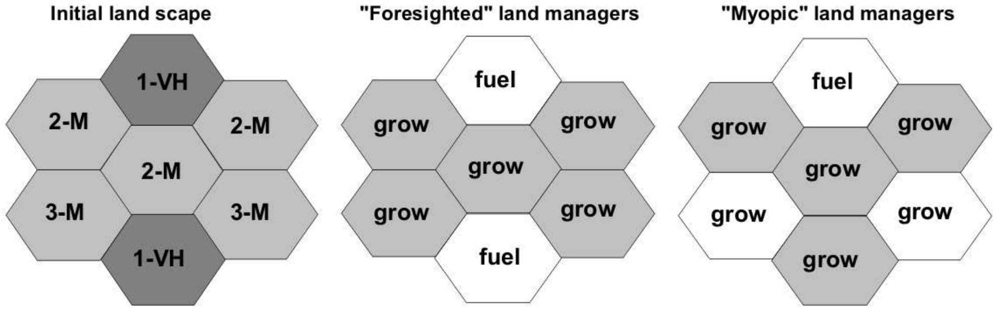
E[$\cdot$]. However, my model allows only two actions: harvest or growing, during the 2nd period. Both types of land mangers will not harvest in the event of fire and will not obtain values from the MU which has burned. In this case, no positive value of information is generated. It is necessary to have a mechanism which enables a "foresighted" land manager to search for an alternative decision. With this mechanism the value of information becomes positive and the best decision will deviate from the decision made by a "myopic" land manager.

In order to generate a positive expected value of information, I assume that once fire occurs, depending on the size of the fire (i.e. the number of MUs burned), the supply of timber will change. Furthermore, I assume a down-sloping demand function and I assume that the price of timber depending on supply. A land manager would face a down-sloping demand function if a land manager has market power (i.e. timber supplied from this landscape are large enough to affect stumpage price).

Therefore, the more MUs burned, the higher the stumpage price becomes. This price change makes alternative harvest patterns attractive in the event of fire and makes the expected value of information positive. Price changes provide a mechanism which makes a "foresighted" land manager search for an alternative harvest pattern in the event of fire.

In order to address this issue I assume the following initial spatial fuel configuration (Figure 4.12). In this landscape MU2, MU4 and MU6 all have age class two, which will be merchantable in the 2nd period. This setting is important because MUs of age class two will be available for harvesting in the 2nd period and therefore, it provides a way to make up a financial loss in the event of fire. Assume that only three MUs can be treated due to budget constraints.

A "foresighted" land manager assigns fuel treatments on MU0 and MU3 (Figure



Fuel Condition Class				
VL = Very Low	L = Low	M = Medium	H = High	VH = Very High

Actions			
cut = harvest	cut&fuel = harvest and fuel treatment	fuel = fuel treatment	grow = grow only

FIGURE 4.12: Spatial configuration of age class and fuel condition class for initial landscape (labeled "age class - fuel condition") and spatial configuration of optimal decisions for two different land managers (labeled "action")

4.12), while a "myopic" land manager assigns fuel treatments on MU1, MU3 and MU5 (Figure 4.12)

For both types of land managers, if no fire occurs, harvesting two MUs (MU1 and MU5) will be optimal in the 2nd period because MU1 and MU5 will become age class 4 in the 2nd period, while MU2, MU4 and MU6 will become age class 3. If one of these two MUs (MU1 and MU5) is damaged and value is lost by fire, a "foresighted" land manager recognizes that he or she will adjust his or her decisions in order to mitigate the loss of value due to fire in the current decision period. In this case, if either MU1 or MU2 is lost to fire, a "foresighted" land manager will choose to cut two of three MUs (MU2, MU4 and, MU6). Therefore, a "foresighted" land manager will cut a total of three MUs to make up for the loss. Harvesting two additional MUs becomes profitable because the temporary price change after fire. However, a "myopic" land manager does not recognize the possibility of mitigating the loss of values in the event of fire in the current decision period. Therefore, a myopic land manager assigns more fuel treatments compared with a foresighted land manager. By treating one of the MUs with a very high spread rate (MU3) and treating the two valuable MUs which are adjacent to the MU with a very high spread rate, a "myopic" land manager achieves the maximum expected NPV when no adjustment of actions is allowed. A "myopic" land manager over-reacts to the risk of fire and tries to protect MUs from fire by assigning more fuel treatments rather than taking advantage of price changes.

4.7. Discussion

In this chapter, I examine how both spatial and stochastic aspects of fire management can provide an insightful framework from which a land manager can investigate factors that contribute to spatial fuel treatment efforts and harvest patterns. My analysis has several distinguishing features that have not been modeled simultaneously in previous studies. First, I employ a hypothetical landscape consisting of seven hexagonal management units (MUs) rather than the commonly used two MUs. Because fire spreads over a landscape and because the spatial layout of fuel treatment affects that spread, the two MU structure does not provide sufficient complexity. Second, whereas earlier studies have focused on the timing of harvest, in this study I examine four actions, including "harvest", "harvest and fuel treatment", "fuel treatment", and "growing" in each of seven MUs. Third, in this study, each decision (i.e. spatial allocation of the actions described above) will lead to many possible spatial fire patterns because of the stochastic nature (i.e. ignition location and weather conditions during fire event) of fire events. Fourth, in this study I examine a variety of initial spatial configurations including both homogeneous and heterogeneous (in terms of fuel conditions) landscapes. Lastly, I compare the behavior of both a "myopic" land manager and a "foresighted" land manager using two different equations rather than examining only one type of land manager as in other studies. The comprehensiveness of this study brings out several important insights. To illustrate the insights, numerical solutions are derived using a specific set of economic and physical parameters.

4.7.1. Spatial Externality

Numerical results demonstrate that spatial externality leads to several general strategies for cost effective spatial allocation of fuel management. One strategy involves locating fuel treatments in MUs in such a way as to separate two or more MUs with very high spread rates. This strategy limits the spread of fire with the treated MU creating a positive spatial externality by limiting risk to other MUs. Wildfire scientists have argued that it is important to disrupt fire growth by disconnecting fuel contiguity at the landscape level [14] [46]. My numerical results indicate that disconnecting fuel contiguity of high spread rates is also economically (financially) desirable.

The results also demonstrate that it is not always necessary to treat a "generator"- the source of the spread of fire - of a large negative spatial externality in order to manage risk across the landscape. The results indicate that the risk of fire damage in each MU is mitigated by a spatial layout of fuel treatment efforts. Therefore, a decision which involves leaving MUs with high spread rates untreated may be optimal if the decision to do so mitigates the risk of fire loss through treating other MUs and, therefore, the loss of expected value is minimized.

The results also show that the rotation age is shortened less and may even be lengthened as opposed to the study by Reed [5] due to spatial externality. There is an incentive to hold timber longer because a standing forest reduces the risk of fire on adjacent MUs, as compared to a recently harvested MU. This result occurs because fire spreads faster in recently harvested stand, as argued by wildfire scientists [12] [13]. Because Reed used a single stand model that does not consider the spread of fire, his model did not recognize the negative impact of harvest on the adjacent stands.

These results indicate that an optimally managed system that accounts for spatial interactions can be quite different from a managed system that assumes independent MUs. The results provide insights into an optimal configuration of fuel management and harvest across homogeneous and heterogeneous landscapes, where similar MUs are often treated differently due to their location.

4.7.2. The Center MU

The analyses identify the nature of important MUs and important spatial patterns, which must be protected or maintained. The results indicate that it is important to protect the center MU because the center MU plays an important role in the spread of fire. Conducting fuel treatment on this center MU will often reduce the risk of value loss in multiple MUs simultaneously, which is important for cost effective fuel management because treating the center MU will yield a large increase in the discounted expected revenue.

In a landscape which consists of thousands of MUs, the center MU is analogous to the MU which is repeatedly burned for multiple fire simulation runs in the sense that the repeatedly burned MU is on the path for many fires. The results suggest that if a land manager can identify these repeatedly burned MUs through a number of fire simulation runs, then these MUs get a higher priority for fuel treatment.

4.7.3. On-site Value Protection and Prevention of the Spread of Fire

A land manager faces spatially explicit trade-offs - trade offs between protection of on-site value (protection of valuable MUs) from fire and prevention of fire spread (treatment of MUs with high spread rates) - in deciding the optimal spatial allocation of fuel management efforts. Because of the higher benefits of protection of valuable MUs, a land manager generally has more incentive to assign fuel treatment to valuable MUs. However, threat of significant value loss caused by the spread of fire encourages the implementation of fuel treatment in less valuable MUs with high spread rates. One decision will dominate the other depending on initial spatial configurations. For example, when a land manager has a landscape that is prone to a significant value loss, he or she is better-off focusing efforts on protecting the landscape from the spread of fire.

4.7.4. "Rule of Thumb" Strategies - Second-Best Solutions

Because "rule of thumb" strategies ignore spatial components of systems, when spatial externality affects action, "rule of thumb" strategies deviate from the optimal strategy. I compare an optimally managed landscape, which takes into account spatial externality, and a landscape managed by using a "rule of thumb" strategy, which is the second best strategies when an appropriate framework cannot be applied due to, for example, high transaction costs or a lack of information. My results show that second best strategies, ("rule of thumb") can be sub-optimal and the differences between the optimal strategy and second-best strategies can be substantial when 1) "rule of thumb" strategies leave connected multiple MUs of high spread rates untreated and 2) failing to treat valuable MUs lowers the expected NPV.

4.7.5. Ignore Spatial Endogenous Risk

When the fire pattern is just one of many possible fires that could occur, the optimal decision for a particular fire pattern becomes suboptimal because generating the optimal decision for a particular fire pattern overlooks trade-offs between risks of value loss, benefits of harvest, and costs of fuel treatment. Assumption of a particular fire decouples the spatial decision from the decision under uncertainty. Then, the current period decision making process becomes the 2nd stage decision where only the trade off between costs and benefits are involved. Current period decisions must involve trade offs between costs, risks and benefits if we do not assume a known fire pattern. When the target fire is one of many possible fires, assuming a target fire and failing to addressing spatial endogenous risk can increase management costs, because the spatial allocation of fuel management efforts generated for the target fire will not be effective in mitigating the risk of fire damage for different fire patterns. Because my framework addresses a wider solution space through consideration of other fire patterns, decisions involve evaluation of spatial arrangements of fuel treatment under many scenarios (i.e. fire patterns). When a decision does not mitigate the risk of fire damage for other possible fire patterns, the decision yields the lower objective value and becomes sub-optimal. My framework generates efficient solutions in cases where it is unknown which fire pattern will occur.

4.7.6. Homogenous and Heterogeneous Landscape

Although many studies assume a single initial spatial configuration which is often homogeneous in terms of fuel conditions [7] [51], considerable amount of interesting behavior over space would be overlooked without examining multiple heterogeneous landscapes. Assumptions of a homogeneous landscape cause us to overlook 1) the fact that real landscapes rarely consist of uniform fuel conditions and, 2) the fact that efficient management efforts may vary depending on spatial arrangements of different fuel conditions and, 3) the fact that a land manager behaves over space in response to the relative values and the risk of value loss in each MU. In a homogeneous landscape, it is not possible to understand that different actions will be required for different fuel conditions and age classes. Also, with a homogenous landscape consisting of only valuable MUs, the model cannot address spatial externality which is generated from an untreated MU with a high spread rate. In this study, I generate many possible initial spatial configurations and search for the optimal decision in each case, which allows me to draw general management implications for implementing cost effective spatial allocation of fuel management.

My results demonstrate that in a landscape with homogeneous fuel conditions, all MUs should not always be treated in the same way. A corner solution is not desirable because it leads to either too much protection or too little protection

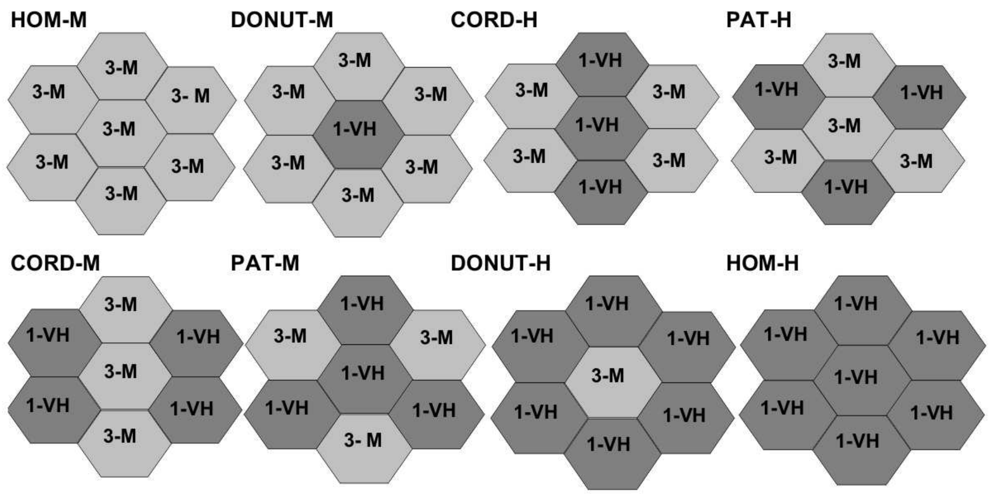
4.7.7. "Myopic" Land Managers and "Foresighted" Land Managers

"Myopic" land managers overreact to the risk of value loss by fire damage because they do not consider the role of forthcoming information in current decisions. "Myopic" land managers tend to assign more fuel treatments than "foresighted" land managers. Differences in their optimal decisions arise when forthcoming information is valuable as in the case when future price changes depend on the amount of timber harvested. The more MUs burned, the higher the stumpage price becomes. This price change increases the value of harvest and helps "foresighted" land managers to mitigate a loss of value in the event of fire by making an alternative harvest pattern available. However, this mechanism does not function in the decision-making process for "myopic" land managers so that they cannot mitigate a loss of value in the event of fire, which leads to the strategy of more fuel treatments.

5. SENSITIVITY ANALYSIS

In this section, I conduct sensitivity analyses on both economic and physical parameters. The purpose of conducting these analyses is to investigate various physical and economic environments and to evaluate how sensitive decisions are to particular parameter values. Although I examine a number of possible initial spatial patterns in Ch.4, here, I examine eight landscapes for easing exposition. Figure 5.1 shows these eight different initial spatial configurations, consisting of four pairs of complementary landscapes which represent the central spatial characteristics of fuel conditions. The first pair consists of two homogenous landscapes, one where all MUs have very high spread rates (hereafter denoted as HOM-H) and the other where all MUs have medium spread rates (hereafter denoted as HOM-M). The other six landscapes are heterogeneous because heterogeneous fuel conditions generate interesting and complex spatial interactions. The first pair of heterogeneous landscapes consists of two donut-shaped landscapes. In these landscapes, an MU with one kind of fuel condition is surrounded by MUs of a different fuel condition. One of the pair of donut-shaped landscapes consists of an MU with a very high spread rate located in the middle of valuable MUs with medium spread rates (hereafter denoted as DONUT-M) (Figure 5.1). The other donut-shaped landscape consists of an MU with a medium spread rate located in the middle of MUs with very high spread rates (hereafter denoted as DONUT-H) (Figure 5.1). The second pair of heterogeneous landscapes consists of two landscapes with a corridor in the middle lane. In these landscapes, a corridor of MUs with one kind of fuel condition separates the outside MUs which have a different fuel condition. One of the pair of corridor landscapes has a corridor of MUs with very high spread rates separating valuable MUs (hereafter denoted as CORD-H) (Figure 5.1).

The other corridor landscape has a corridor of MUs with medium spread rates (hereafter denoted as CORD-M) (Figure 5.1). The last pair of heterogeneous landscapes consists of two patchy landscapes. In these landscapes, MUs with one kind of fuel condition are isolated from each other by MUs with a different fuel condition. One patchy landscape has three isolated valuable MUs with medium spread rates (hereafter denoted as PAT-M) (Figure 5.1). The other patchy landscape has three isolated MUs with very high spread rates (hereafter denoted as PAT-H) (Figure 5.1).



Fuel Condition Class				
VL = Very Low	L = Low	M = Medium	H = High	VH = Very High

FIGURE 5.1: Eight initial landscapes (labeled ”age class - fuel condition”)

5.1. Economic Parameters

The economic parameters include discount rate, fuel treatment cost, stumpage price, and regeneration cost. I vary the parameters one at a time, leaving all others at base values in order to analyze the impact of a single factor in the economic environment on the optimal decision. This comparative static analysis approach allows me to test results against well established economic theory.

5.1.1. Discount Rates

The base case uses a discount rate of 4%. I evaluate how the optimal decision varies with the discount rate ranging from 0.01% to 9%. I assume that any given discount rate is constant over the decision time frame. Figure 5.2 and Figure 5.3 depict how the optimal decision changes in accordance with different discount rate levels. In the figures, the discount rate increases from left to right. The optimal decision for the base parameter value is surrounded by a circle.

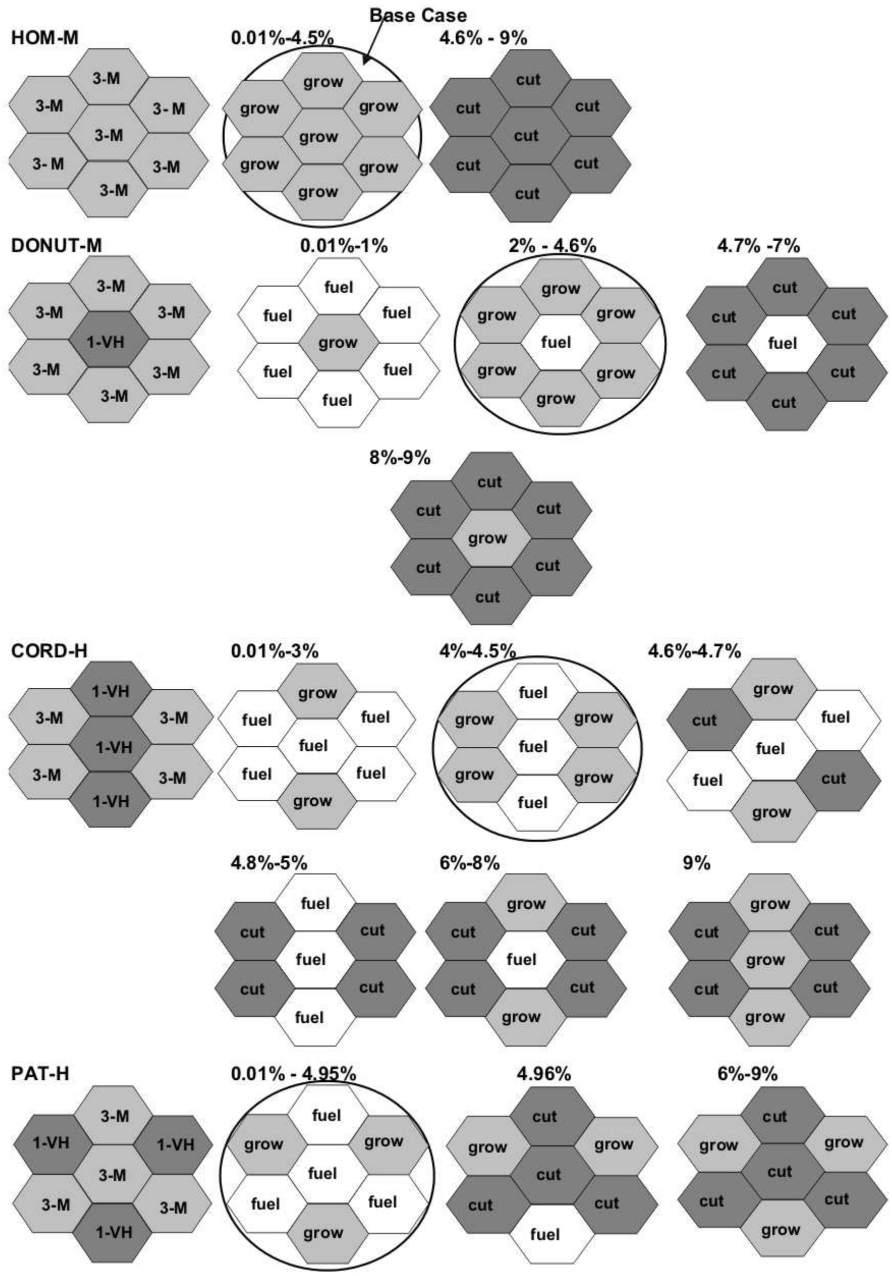
For a non-spatial stand level model, it is well established that higher discount rates shorten the optimal rotation age [56] [40] [57] [58] [59].

Generally at higher discount rates, a land manager harvests more MUs with merchantable timber during the current period because of the higher opportunity cost of holding timber (Figure 5.2 and Figure 5.3). A land manager harvests all MUs with merchantable timber at a discount rate of around 5% (Figure 5.2 and Figure 5.3).

A land manager treats less MUs at higher discount rates because higher discount rates make the value gained in the future less significant, and it is more likely that additional fuel treatment costs will not be offset by an increase in the expected NPV. A land manager does not assign fuel treatments in any MU at a discount rate of 9% or higher (Figure 5.2 and Figure 5.3).

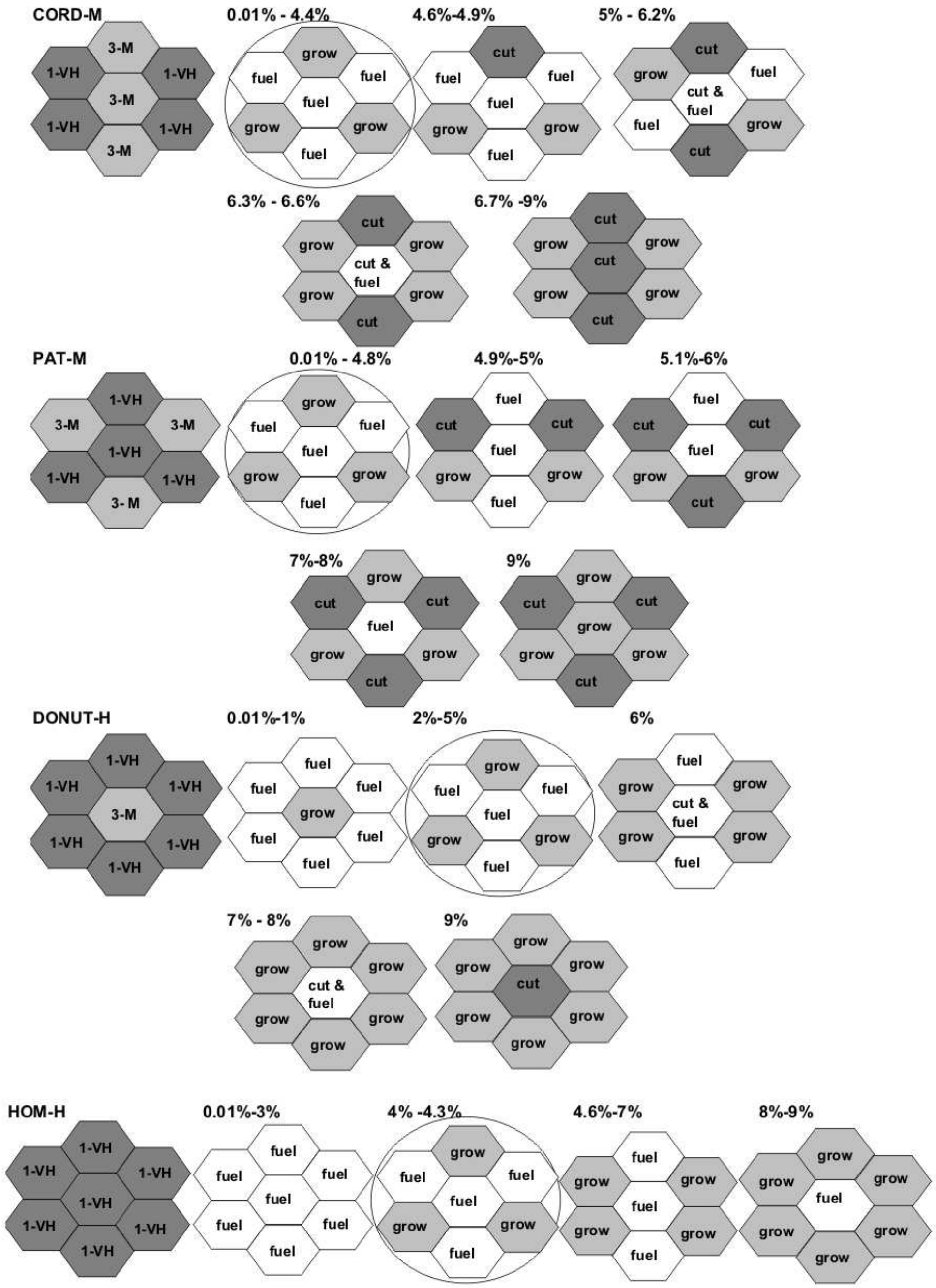
Although these results are consistent with a traditional stand level analysis, an interesting harvest pattern was found by combining a spatial and dynamic model together. The results show that harvesting some but not all economically valuable MUs becomes optimal (CORD-H at discount rate 4.6%- in Figure 5.2, CORD-M at discount rate 5%- in Figure 5.3 and PAT-M at discount rate 4.9%- in Figure 5.3). This heterogeneous harvest pattern within age classes becomes optimal because harvesting an MU without treatment will increase the spread rate in that MU and increase the risk of fire in that MU as well as in adjacent MUs. A land manager can fully take into account the impact of spatial externality by treating valuable MUs, which are next to harvested MUs.

The findings from this analysis can be summarized in the following: At higher discount rates, a land manager harvests more during the current period due to the opportunity cost of holding timber. Because harvesting will increase the risk of value loss by fire damage in adjacent MUs, more harvesting will encourage the implementation of fuel treatment. However, because the future value obtained in each MU is lower at higher discount rates, the value that a land manager tries to protect through fuel treatment is lower at higher discount rates. Then, it becomes more difficult to justify the cost of fuel treatment. Therefore, there is less incentive to assign fuel treatment. At a high enough discount rate, the value gained from fuel treatment is too small and it is not worth treating MUs.



Actions			
cut = harvest	cut&fuel = harvest and fuel treatment	fuel = fuel treatment	grow = grow only

FIGURE 5.2: Optimal decisions for different discount rates (labeled "action")



Actions			
cut = harvest	cut&fuel = harvest and fuel treatment	fuel = fuel treatment	grow = grow only

FIGURE 5.3: Optimal decisions for different discount rates (labeled "action")

5.1.2. Fuel Treatment Costs

The base case uses a fuel treatment cost of $200/acre. Fuel treatment cost ranges from around $50/acre to over $1000/acre depending on the type of stand to be treated [55]. I evaluate how the optimal decision can vary across fuel treatment costs of $50/acre to $1400/acre. Figure 5.4 and Figure 5.5 depict how the optimal decision changes in accordance with different fuel treatment costs. The cost of fuel treatment increases from left to right.

The general trend is that at higher fuel treatment costs, a land manager treats less MUs (Figure 5.4 and Figure 5.5). At higher fuel treatment costs, the expected NPV after treatment has to be high enough to recover this high cost. At a high enough fuel treatment cost, the cost is too high so that a land manager does not treat any MU (Figure 5.4 and Figure 5.5).

However, the highest cost that a land manager pays for a single treatment can be case specific. For example, in landscape DONUT-M (Figure 5.4), a land manager assigns a single treatment on the center MU at $1300/acre, while in other landscapes a land manager assigns a single treatment at $400 - $600/acre and when the fuel treatment cost is higher than those, no fuel treatment is assigned.

Various costs for a single treatment occur because the "spread protection value" - how much the expected NPV increases from treatment of a single MU - depends upon spatial configurations. Treating a single MU is worth more for one landscape than for another.

For example, landscapes CORD-H (Figure 5.4) and PAT-M (Figure 5.5) are compared in terms of the cost of protecting the center MU. The sensitivity analyses show that a land manager pays the higher cost for protecting a single MU, which is the center MU, for PAT-M. In landscape PAT-M, protecting a single MU (which happens to be the center MU) disconnects two contiguities of MUs with high spread rates (Figure 5.5), while in landscape CORD-H protecting the center MU will disconnect a single contiguity of high spread rates (Figure 5.4). The risk reduction by protecting the center MU is larger for PAT-M. Therefore, ”spread protection value” of the center MU is higher for PAT-M and a land manager pays the higher fuel treatment cost.

Also, for example, landscape of HOM-H or DONUT-H is covered by very few MUs with merchantable timber (Figure 5.5). Then, not protecting the center MU increases the risk of fire damage in very few valuable MUs. However, in landscape DONUT-M because the landscape is covered by six MUs with merchantable timber (Figure 5.4), not protecting the center MU will increase the risk of fire loss in these six valuable MUs. ”Spread protection value” is higher in landscape DONUT-M and a land manager pays a high cost of fuel treatment of $1300/acre, which is the highest among all eight landscapes (Figure 5.4).

As you may notice from the discussion above or Figure 5.4 and Figure 5.5, when the cost of fuel treatment is high, only the center MU is generally treated. Protecting the center MU disconnects MUs with high spread rates from each other and limits the spread of fire, making the center MU particularly valuable for risk reduction.

However, there is an exception to this ”rule”. Figure 5.5 shows that in landscape DONUT-H, of the fuel treatment costs tested, at higher costs, the optimal decision shifts from treating two outside MUs in the middle lane to doing nothing rather than treating the center MU. At the cost of $419/acre, the optimal decision is to protect the two outside MUs in the middle lane rather than protecting the center MU. At a fuel treatment cost of $420/acre the optimal decision is to do nothing.

When the center MU is surrounded by connected MUs with high spread rates, treating two outside MUs in the middle lane becomes optimal because protecting a single center MU has less impact on reduction of the risk of fire damage. Therefore, the cost of fuel treatment for the center MU cannot be offset by the increase in the expected NPV when the cost of fuel treatment is high (i.e. \$420/acre of higher).

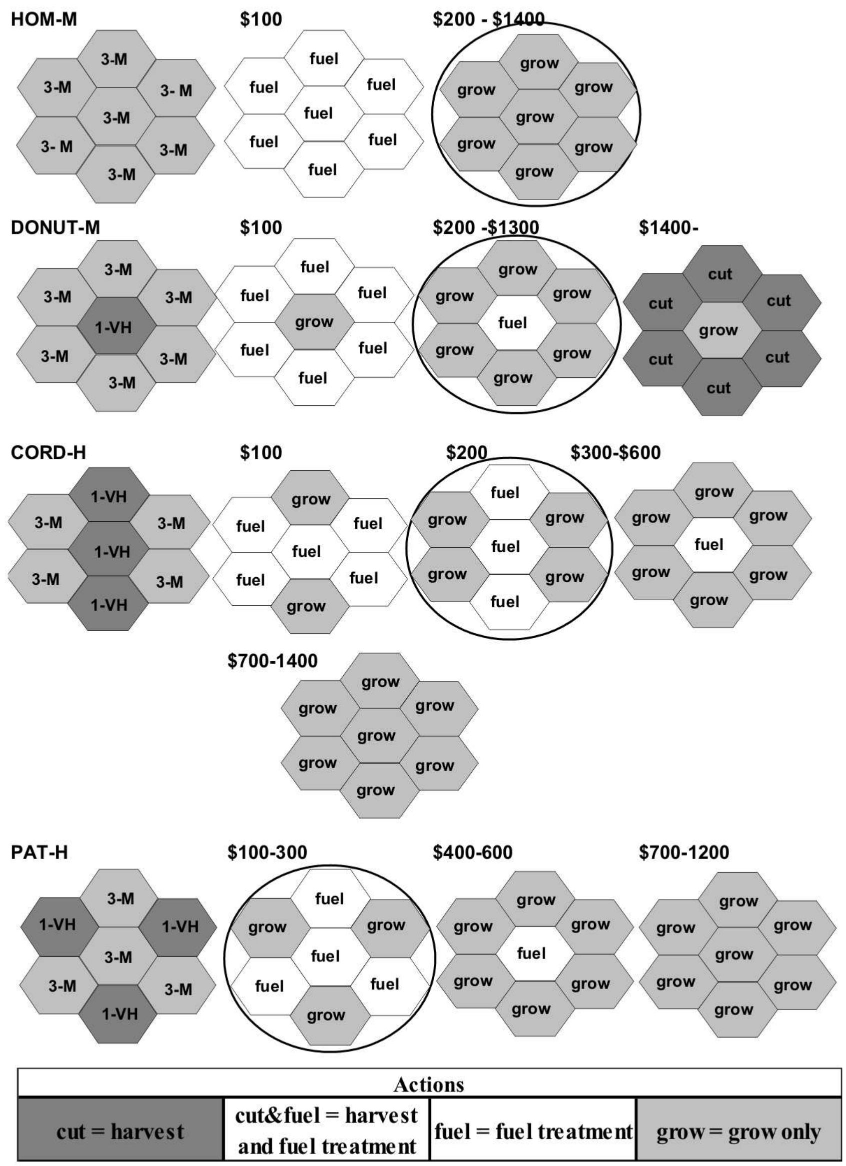


FIGURE 5.4: Optimal decisions for different fuel treatment costs (labeled "action")

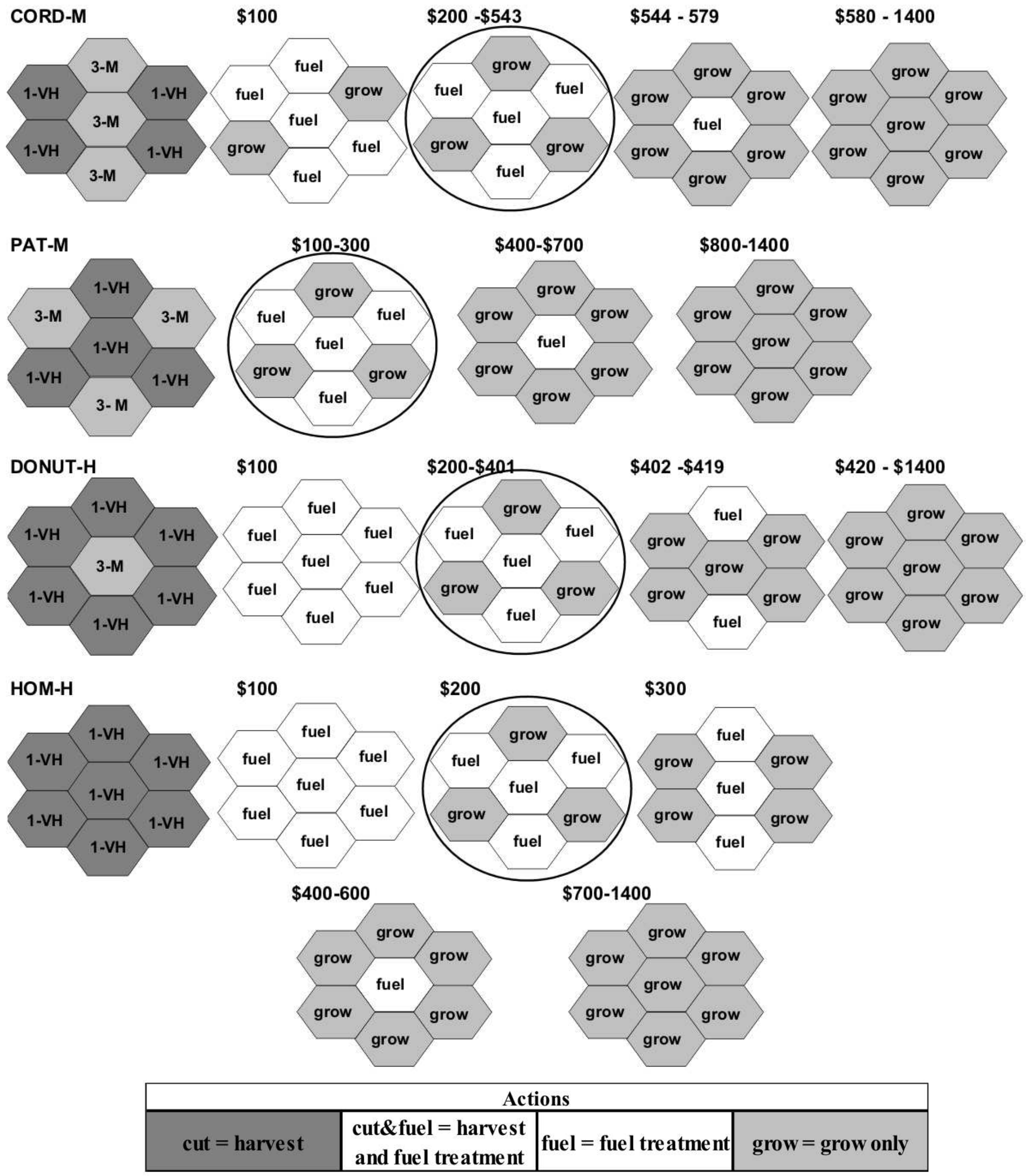


FIGURE 5.5: Optimal decisions for different fuel treatment costs (labeled "action")

5.1.3. Stumpage Price

The base case uses a stumpage price of \$500/mbf. Haynes [60] shows that stumpage price of ponderosa pine has fluctuated from about \$50/mbf to \$600/mbf between the years1973 to 1995[9]. I evaluate how the optimal decision varies with the stumpage prices ranging from \$100/mbf to \$1000/mbf. I assume that stumpage price is constant over the decision time frame. Figure 5.6 and Figure 5.7 depict how the optimal decision changes in accordance with different stumpage prices. The stumpage price increases from left to right.

At higher stumpage price, a land manager assigns more fuel treatment while at lower stumpage price he or she assigns less fuel treatment (Figure 5.6 and Figure 5.7).

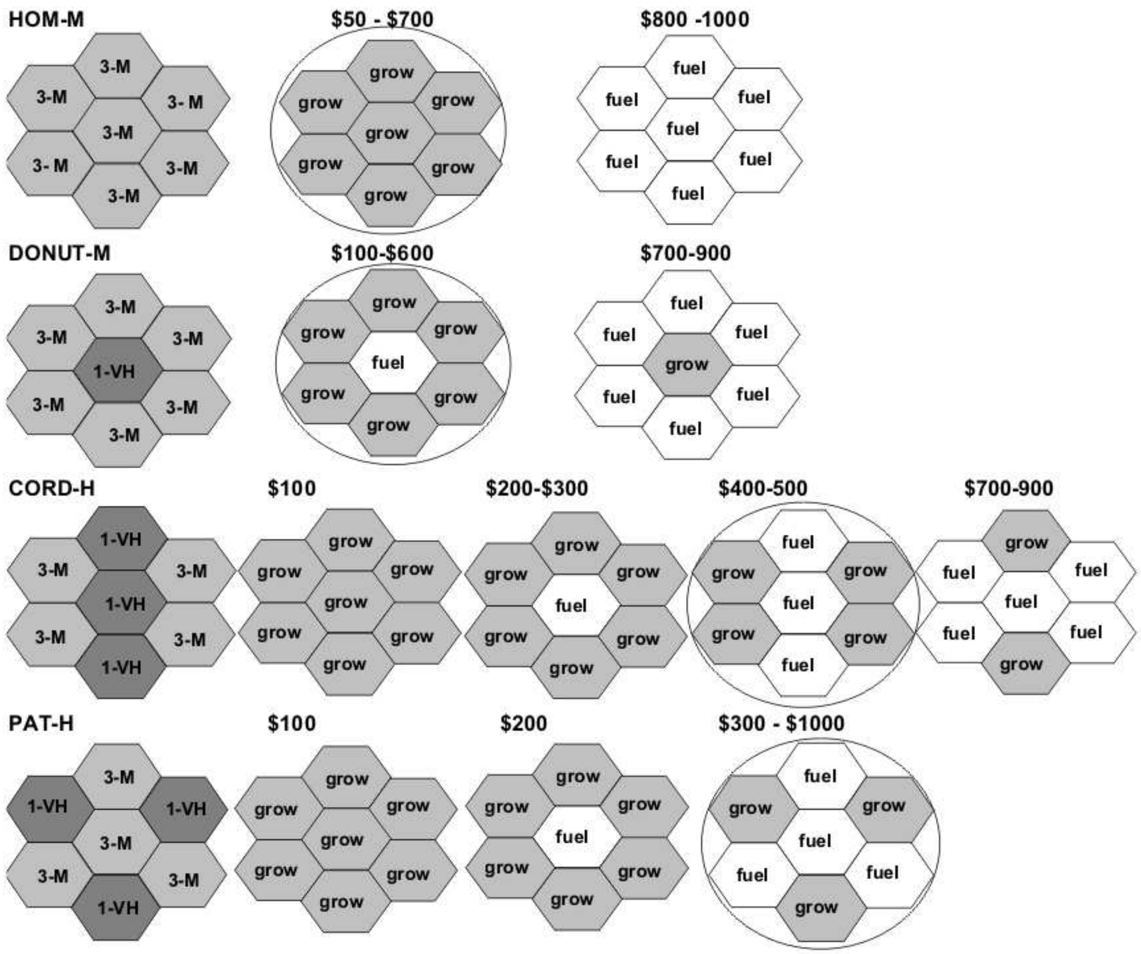
At higher stumpage prices, the value of fuel treatment is high because fuel treatment will protect high value as stumpage price increases. It is more likely that the cost of additional fuel treatments will be recovered. At a high stumpage price, the value gained from treatment is significant, which provides incentive for a land manager to conduct more treatment. Therefore, more fuel treatments will be assigned.

On the other hand, at lower stumpage prices, the benefits gained from fuel treatments through risk reductions are low. Then, less fuel treatment will be conducted (Figure 5.6 and Figure 5.7). At a low enough price, the value gained from treatment is too small and it is not worth protecting even a single MU.

As the results from sensitivity analyses of fuel treatment cost show, due to spatial interactions a high enough stumpage price level which will allow only a single fuel treatment to be assigned can vary depending on the landscape. For example, when the stumpage price is low at \$100/mbf, it is generally optimal not to assign fuel treatment in landscapes

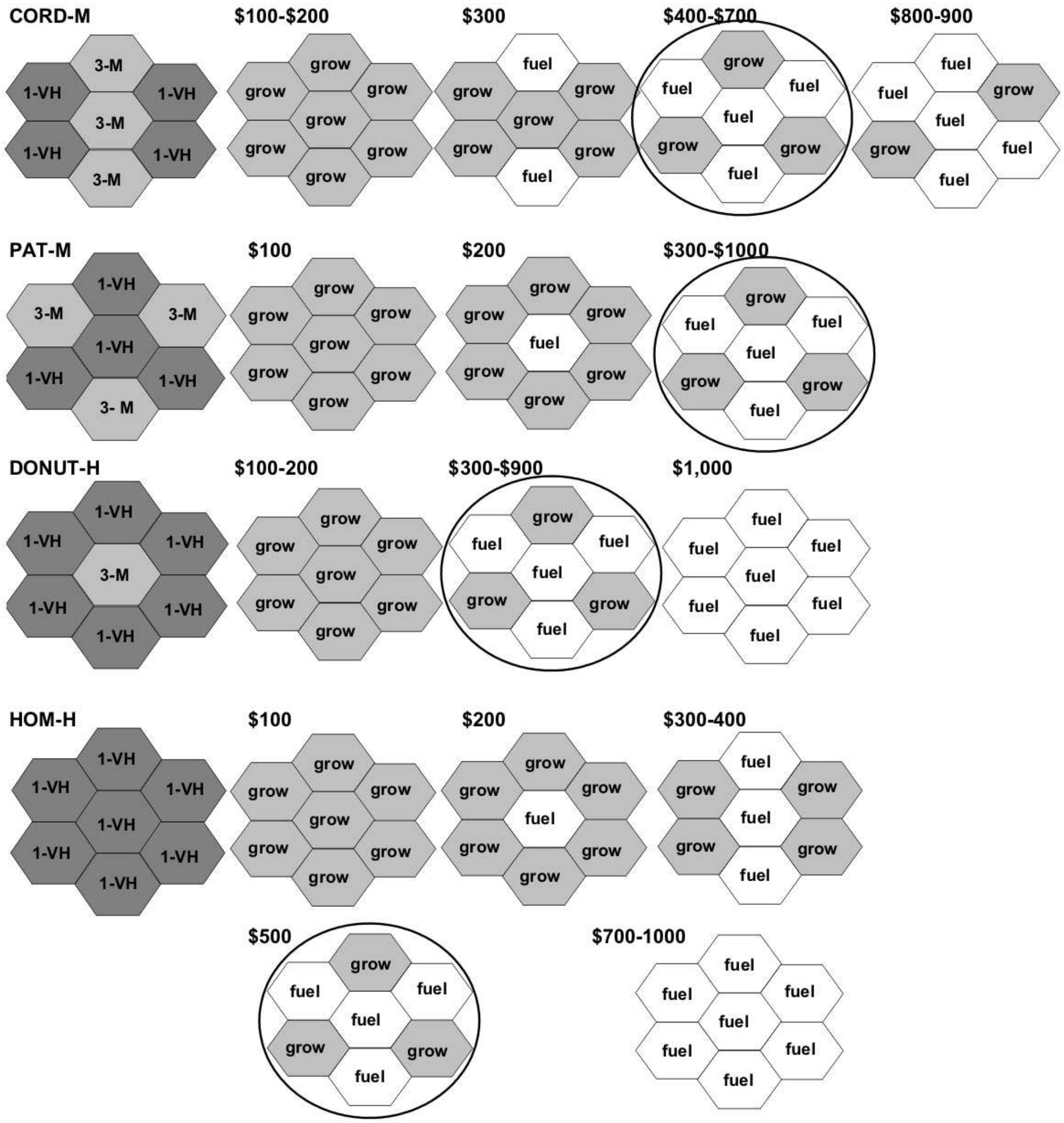
[9]Stumpage prices in Haynes' study are in nominal dollars and are not adjusted for inflation.

(Figure 5.6 and Figure 5.7). However, in landscape DONUT-M, the optimal decision is to treat the center MU at a stumpage price of $100/mbf (Figure 5.6). A land manager assigns fuel treatments at a low stumpage price because in DONUT-M, the center MU which has a very high spread rate is surrounded by valuable MUs of age class 3 (Figure 5.6). Therefore, treating the center MU will reduce the risk of fire loss in each of these valuable MUs, which makes it worth while to treat the center MU. In other words, if the center MU is not treated, reduction of the expected NPV is substantial.



Actions			
cut = harvest	cut&fuel = harvest and fuel treatment	fuel = fuel treatment	grow = grow only

FIGURE 5.6: Optimal decisions for different stumpage prices (labeled "action")



Actions			
cut = harvest	cut&fuel = harvest and fuel treatment	fuel = fuel treatment	grow = grow only

FIGURE 5.7: Optimal decisions for different stumpage prices (labeled "action")

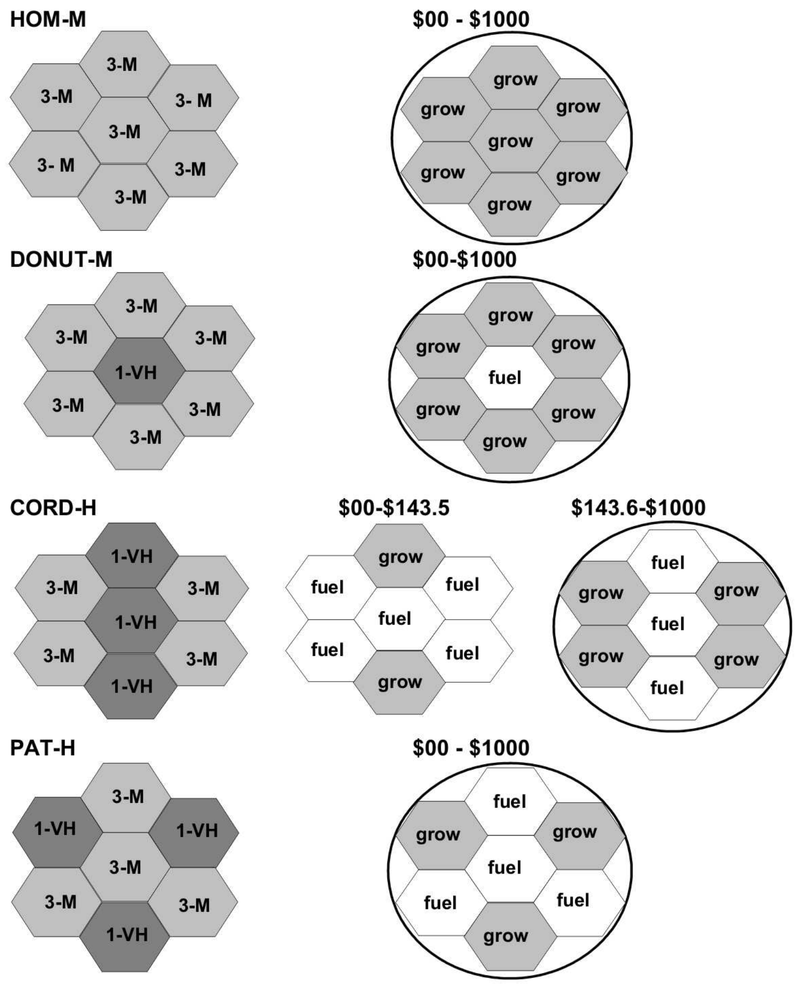
5.1.4. Regeneration Cost

The base case uses a regeneration cost of \$200/acre. Regeneration cost ranges from around \$200/acre to \$1000/acre [61] [62] [63]. I evaluate how the optimal decision will vary with different regeneration costs ranging from \$00/acre to \$1,000/acre. I assume that the cost of regeneration is constant over the decision time frame. Figure 5.8 and Figure 5.9 depict how the optimal decision changes in accordance with different regeneration costs. The cost of regeneration increases from left to right. In this model, there are two cases where these costs are incurred in an MU. The first case is when fire burns an MU during the current period. In this case, regeneration must be conducted. The second case is when a land manager harvests an MU. In this case, regeneration must also be conducted.

The optimal spatial management effort allocation is less sensitive to the cost of regeneration because 1) unlike the stumpage price, regeneration cost is on a per acre basis (stumpage price is on a per mbf basis) and 2) unlike the cost of fuel treatments, the cost of regeneration will be discounted because the optimal decision is to cut timber in the 2nd period at the base case discount rate (4%) and 3) unlike the cost of fuel treatments, the regeneration cost is weighted by the probability of fire damage in an MU. These three factors will make the impact of the regeneration cost on optimal spatial fuel management efforts less significant.

Because at a higher (lower) regeneration cost, the expected NPV is low (high), changes in regeneration cost affects the optimal decision in a similar way as changes in stumpage prices do. However, value changes are less significant compared to those by changing stumpage prices.

In CORD-H, at the lower regeneration cost of \$143.5/acre, a land manager treats five MUs (Figure 5.8). More fuel treatments are conducted because, due to a lower regeneration cost, the cost of additional fuel treatment is offset by the higher expected NPV of harvesting timber. Additional fuel treatment has to reduce the risk of fire loss enough to make it worth the effort. In other landscapes, additional fuel treatment cannot reduce the risk of fire loss enough to make it worth doing (Figure 5.8 and Figure 5.9).



Actions			
cut = harvest	cut&fuel = harvest and fuel treatment	fuel = fuel treatment	grow = grow only

FIGURE 5.8: Optimal decisions for different regeneration costs (labeled "action")

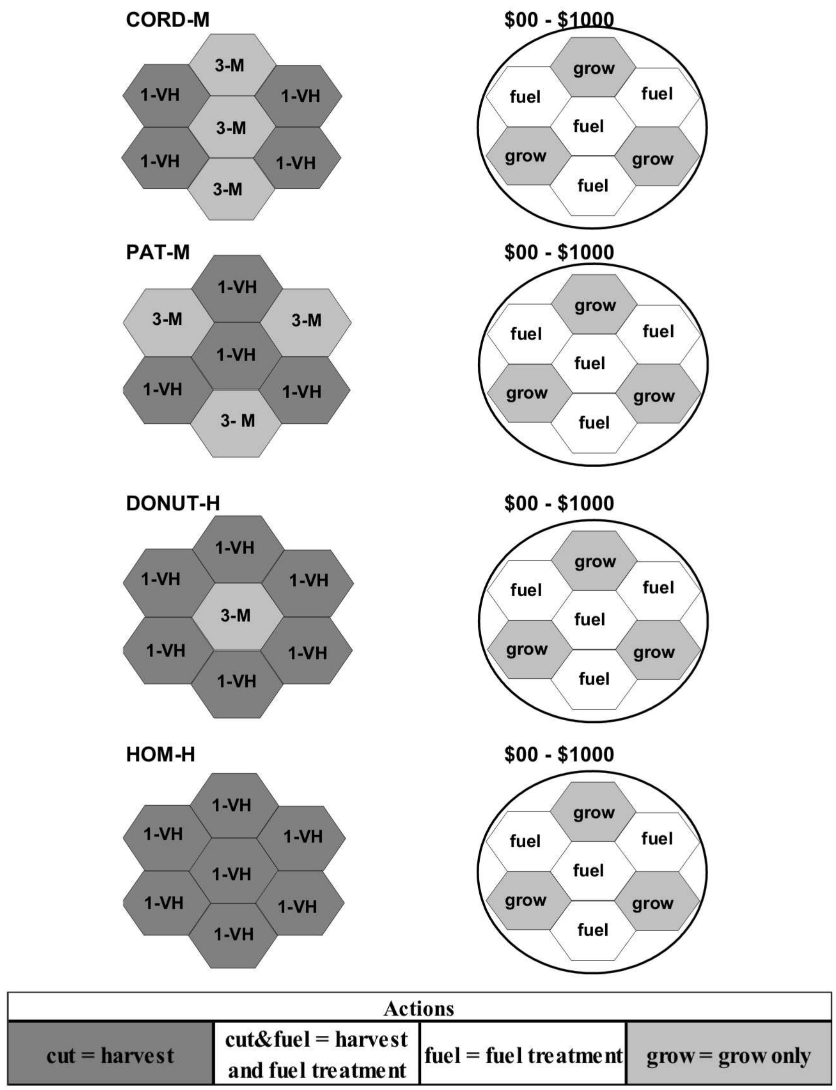


FIGURE 5.9: Optimal decisions for different regeneration costs (labeled "action")

5.2. Physical Parameters

The physical parameters include intensity level of fuel management, frequency of different weather conditions, frequency of fire, and fire duration time. I vary the parameters one at a time, leaving all others at base values in order to analyze the impact of a single factor in the physical environment on the optimal decision.

5.2.1. Intensity Fuel Treatment

The public agency faces the problem of allocating their limited resources to mitigate the risk of fire and, therefore, is interested in questions such as - When and where is it better to treat a broader area with low intensity strategies or treat a limited area? The following analyses of various intensity levels of fuel treatment will provide the basis for evaluating how the agency will allocate high intensity fuel management at a higher cost and low intensity fuel management at a lower cost. To evaluate these cases, I changed the fire spread rates after fuel treatment. To represent low (high) intensity fuel management, higher (lower) spread rates are applied to the treated MUs so that fire spread can be slowed down less (more) effectively.

Low Intensity Fuel Treatment

I evaluate three cases in which the fire spread rates after treatment are 15% higher (hereafter denoted as "low intensity fuel management 1") and 25% higher (hereafter denoted as "low intensity fuel management 2") and 50% higher (hereafter denoted as "low intensity fuel management 3") than in the base case. With low intensity fuel management

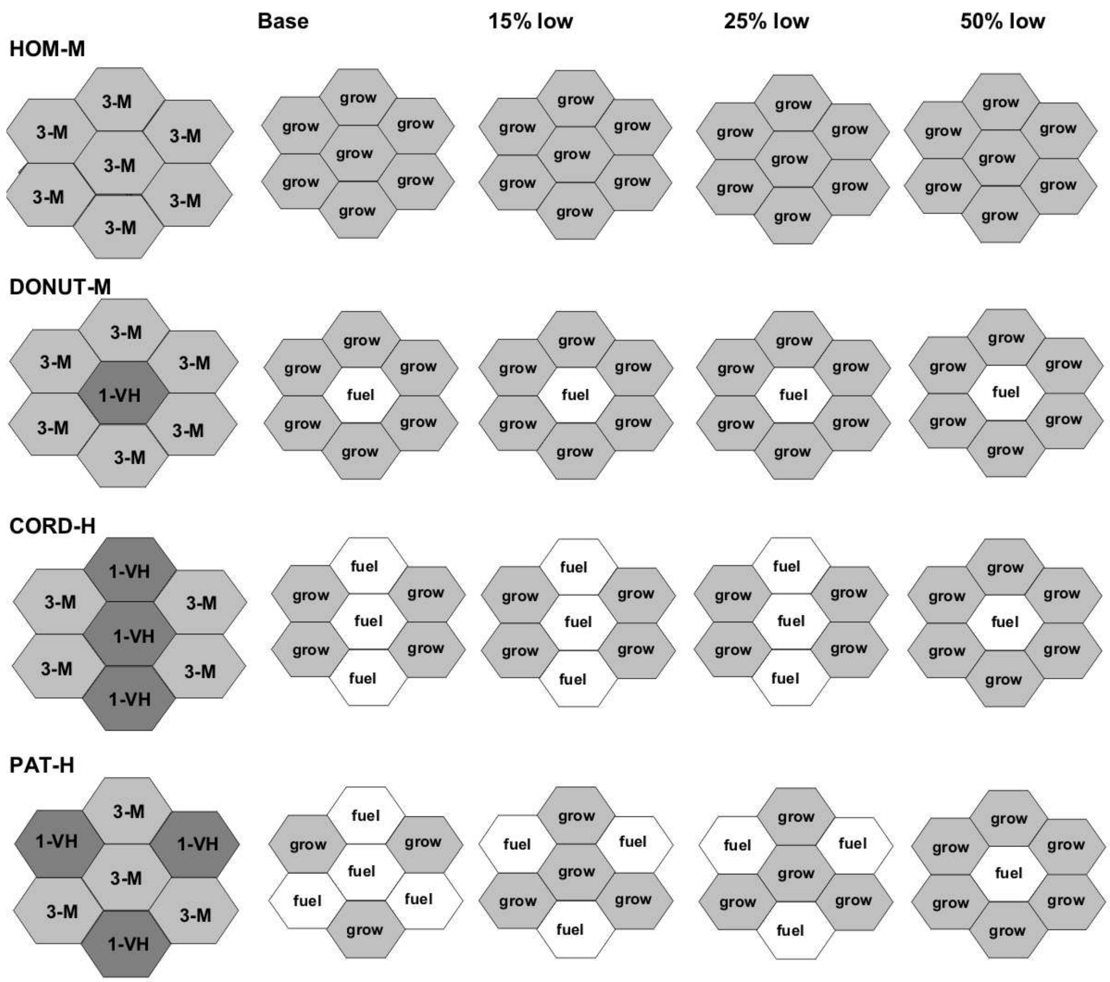
3, treated MUs with age class 3 are burned not only under severe weather conditions but also under mild weather conditions, if they ignite. Therefore, fuel treatment does not reduce the risk of fire loss much in treated MUs. With low intensity fuel management 1 & 2, as the base case, treated MUs of age class 1 are burned under either mild or severe weather conditions, if they ignite. Treated MUs of age class 3 are burned only under severe weather conditions, if they ignite. Figure 5.10 and Figure 5.11 depict how the optimal decision changes in accordance with different fuel intensity levels. In the figures, the level of intensity decreases from left to right. Figure 5.12 and Figure 5.13 depict how the optimal landscape changes in accordance with different fuel intensity levels after the optimal decision is applied.

A land manager treats all MUs with very high spread rates when low intensity fuel management 1 and 2 are applied (Figure 5.10 and Figure 5.11). With low intensity fuel management 1 & 2, treated MUs are burned, if adjacent MUs have high spread rates and ignite because fuel management is less effective. However, with the base case fuel management, if an MU is treated, then fire starting from adjacent MUs with high spread rates does not burn this treated MU. Because less effective fuel management increases the risk of value loss in multiple MUs, a land manager has an incentive to treat MUs with high spread rates, when low intensity fuel management 1 and 2 are applied.

When low intensity fuel management 3 is applied, a land manager treats less MUs (Figure 5.10 and Figure 5.11). A land manager treats only the center MU unless landscapes are fully or almost fully covered by MUs with very high spread rates (Figure 5.11, DONUT-H, HOM-H). A land manager assigns less fuel treatment because fuel treatment is less effective so that even fire starting from the treated MUs can move into the adjacent MUs. The marginal cost of fuel treatment exceeds the marginal expected NPV.

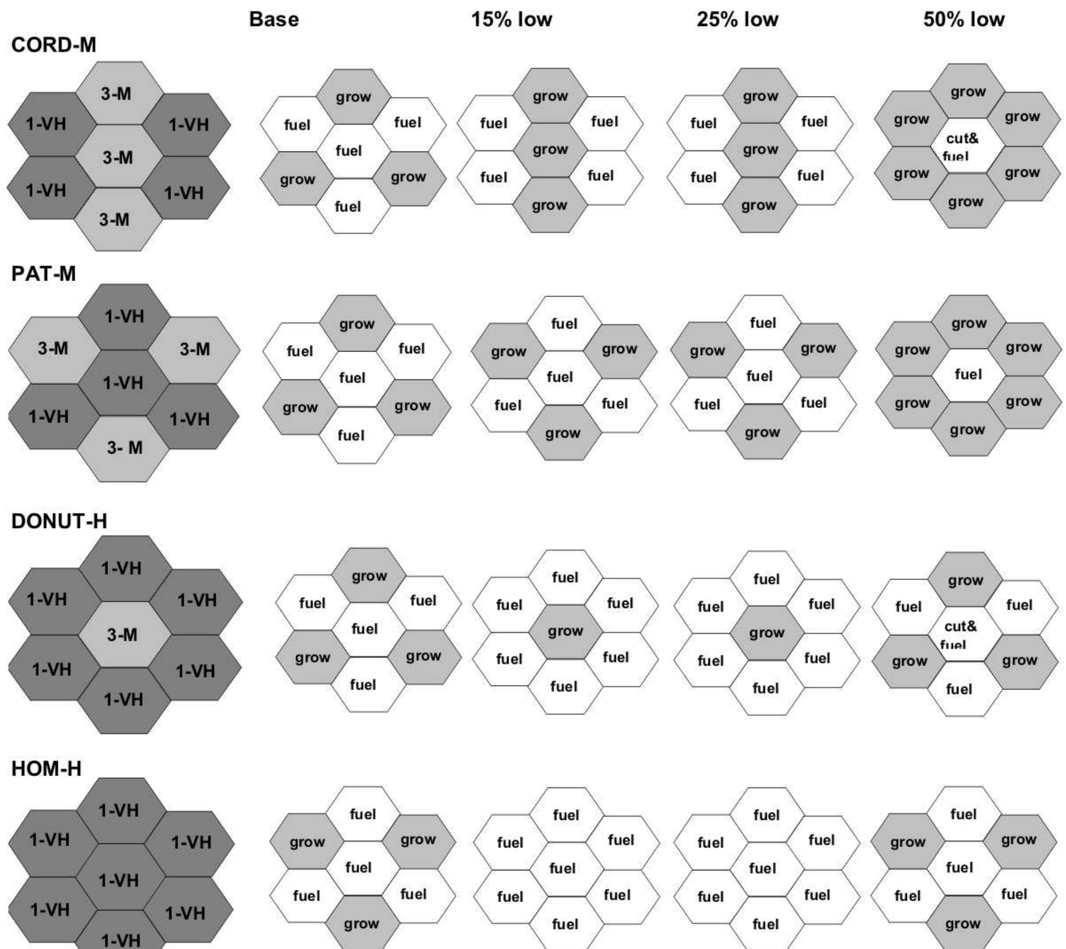
When low intensity fuel management 3 is applied, in landscape HOM-H, a land manager finds that treating all MUs is no better than treating only four MUs in terms of risk reduction (Figure 5.11). However, treating only the center MU is not optimal either because no treatment in MUs with high spread rates will increase the risk of value loss in multiple MUs.

When low intensity fuel management 3 is applied, in landscapes CORD-M, and DONUT-H, where the center MU is surrounded by contiguities of MUs with very high spread rates, a land manager harvests the center MU during the current period because the risk of holding timber in the center MU is high in these landscapes (Figure 5.11).



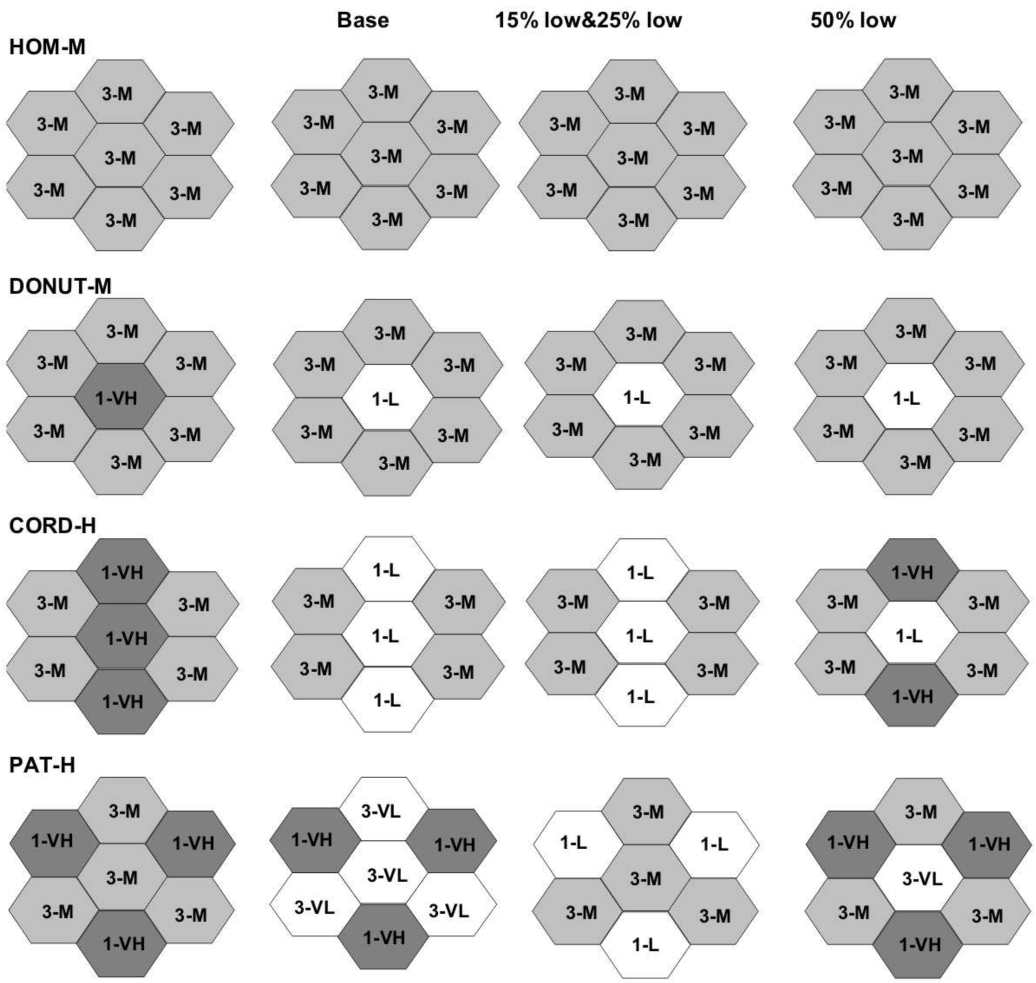
Actions			
cut = harvest	cut&fuel = harvest and fuel treatment	fuel = fuel treatment	grow = grow only

FIGURE 5.10: Optimal decisions for different low intensity levels of fuel treatments(labeled "action")



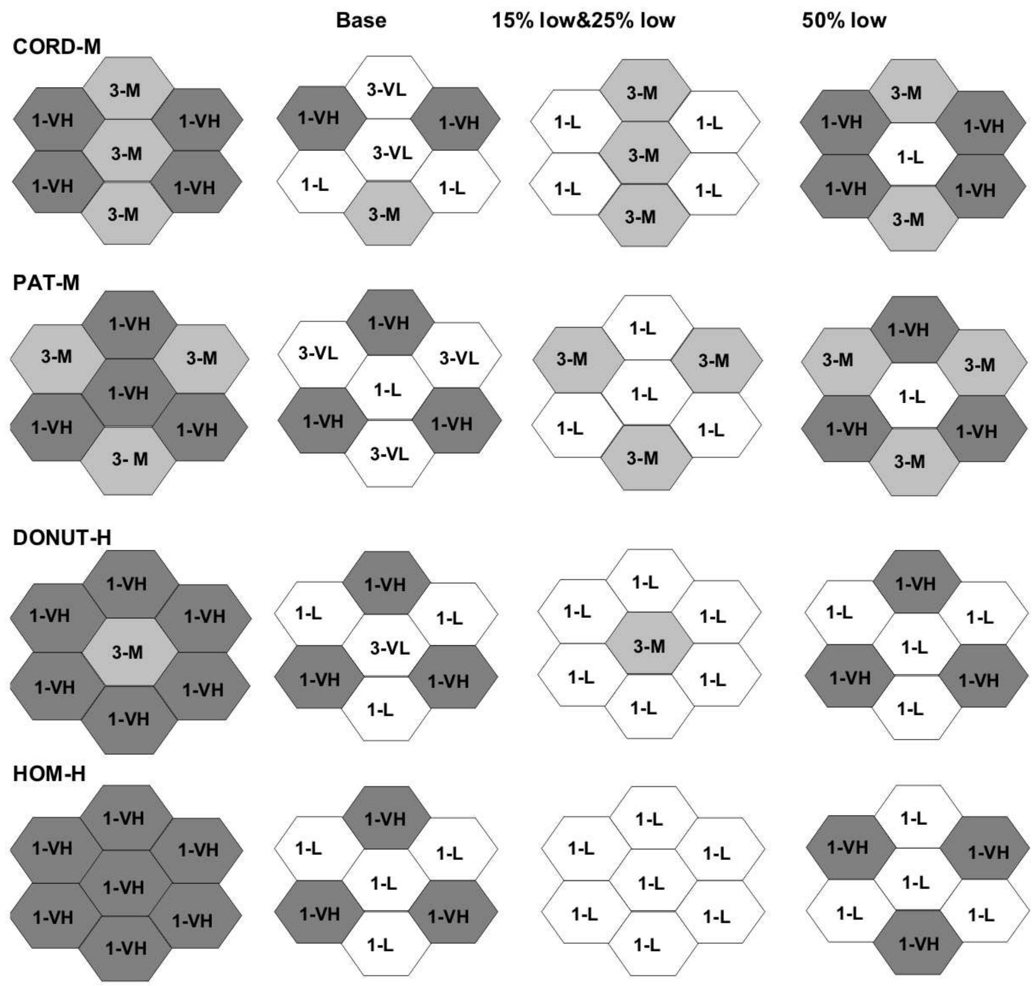
Actions			
cut = harvest	cut&fuel = harvest and fuel treatment	fuel = fuel treatment	grow = grow only

FIGURE 5.11: Optimal decisions for different low intensity levels of fuel treatments(labeled "action")



Fuel Condition Class				
VL = Very Low	L = Low	M = Medium	H = High	VH = Very High

FIGURE 5.12: Optimal landscapes for different low intensity levels of fuel treatments after optimal decision is applied(labeled "age class - fuel condition")



Fuel Condition Class				
VL = Very Low	L = Low	M = Medium	H = High	VH = Very High

FIGURE 5.13: Optimal landscapes for different low intensity levels of fuel treatments after optimal decision is applied(labeled "age class - fuel condition")

High Intensity Fuel Treatment

I evaluate three cases in which the fire spread rates after treatment are 15% lower (hereafter denoted as "high intensity fuel management 1") and 25% lower (hereafter denoted as "high intensity fuel management 2") and 50% lower (hereafter denoted as "high intensity fuel management 3") than in the base case. For the base case, when MUs of age class 1 are treated (fuel condition: "low spread rate"), then these MUs are still burned under either severe or mild weather conditions, if they ignite. When MUs of age class 3 are treated (fuel condition: "very low spread rate"), then these MUs are burned only under severed weather condition, if they ignite.

For high intensity fuel management 1 and 2, when MUs of age class 1, are treated, then these MUs are burned only under severe weather condition, if they ignite. But when MUs of age class 3 are treated, these MUs are still burned under severe weather condition, if they ignite.

For high intensity fuel management 3, when MUs of age class 1 are treated, these MUs are burned only under severe weather condition, if they ignite. When MUs of age class 3 are treated, these MUs are not burned under either severe or mild weather conditions, if they ignite. Therefore, when MUs of age class 3 are treated, the probability of fire damage in these MUs can be reduced to zero. Figure 5.14 and Figure 5.15 depict how the optimal decision changes in accordance with different fuel intensity levels. In the figures, the level of intensity increases from left to right. Figure 5.16 and Figure 5.17 depict how the optimal landscape changes in accordance with different fuel intensity levels after the optimal decision is applied.

Figure 5.14 and Figure 5.15 show that for high intensity management 1 and 2, the optimal decision would be no different from that of the base case. However, for high intensity management 3, a land manager assigns more fuel treatment in some landscapes (HOM-M, DONUT-M and, CORD-H, Figure 5.14), and assigns less fuel treatment in the other landscape (CORD-M) (Figure 5.15).

For example, a land manager treats more valuable MUs in landscapes DONUT-M and HOM-M compared with the base case (Figure 5.15). For the base case, the optimal decision is to assign fuel treatment only in the center MU for landscape DONUT-M, and no fuel treatment for landscape HOM-M (Figure 5.14). For the base case, a land manager assigns less fuel treatment in these landscapes because the marginal cost of fuel treatment exceeds the marginal increase in the expected NPV with the base case fuel management, which is less effective than the high intensity fuel management. In order for more fuel treatment to be considered optimal, the risk in each MU has to be further reduced so that an increase in the expected NPV will be greater and offset the larger cost of treating more MUs. With high intensity fuel management 3, fuel treatments in MUs of age class 3 reduces the risk of fire loss to a lower level than that for the base case. By protecting these MUs, the expected NPV in the future period increases and the larger cost of more fuel treatment is recovered. The marginal increase in the expected NPV exceeds the marginal cost of fuel treatment. As a result, compared with the base-case, more MUs are treated in these landscapes.

Also, in landscape CORD-H, a land manager assigns more fuel treatments (Figure 5.14). The base-case optimal decision is to treat three MUs of age class 1 in the middle lane. However, with intensity fuel management 3, a land manager can obtain a higher expected NPV by treating all four MUs of age class 3 and the center MU.

On the other hand, in landscape, CORD-M, a land manager assigns less treatment. In CORD-M, the optimal decision for the base case is to treat four MUs including two MUs of age class 3 and two MUs of age class 1. This decision yields a landscape where

MUs of very high spread rates are separated. However, with intensity fuel management 3, treating all MUs of age class 3 in the middle lane reduces the risk of fire loss significantly and, therefore, even though the risk of fire loss in MUs of age class 1 in the outer lanes increases, reduction of the risk of fire loss in these three valuable MUs and the lower cost of less fuel treatment offset the loss of values from MUs of age class 1 and increases the expected NPV. Therefore, the decision to treat only three MUs in middle lane yields a higher expected NPV.

Figure 5.16 and Figure 5.17 show that with high intensity fuel management 3 the optimal decision yields a landscape containing more MUs with very low spread rate, which means that a land manager assigns fuel treatment on MUs of age class 3 (MUs labeled "3-M"). More valuable MUs are protected because when MUs of age class 3 are treated, these MUs are not burned under either severe or mild weather conditions, if they ignite (by treating MUs of age class 3, the risk of value loss in these MUs is reduced to zero). Fire starting from one MU does not damage adjacent MUs of age class 3, if they are treated. Therefore, when fuel treatment is effective, the spread of fire will not be an issue and a land manager focuses his or her management effort on protection of on-site value.

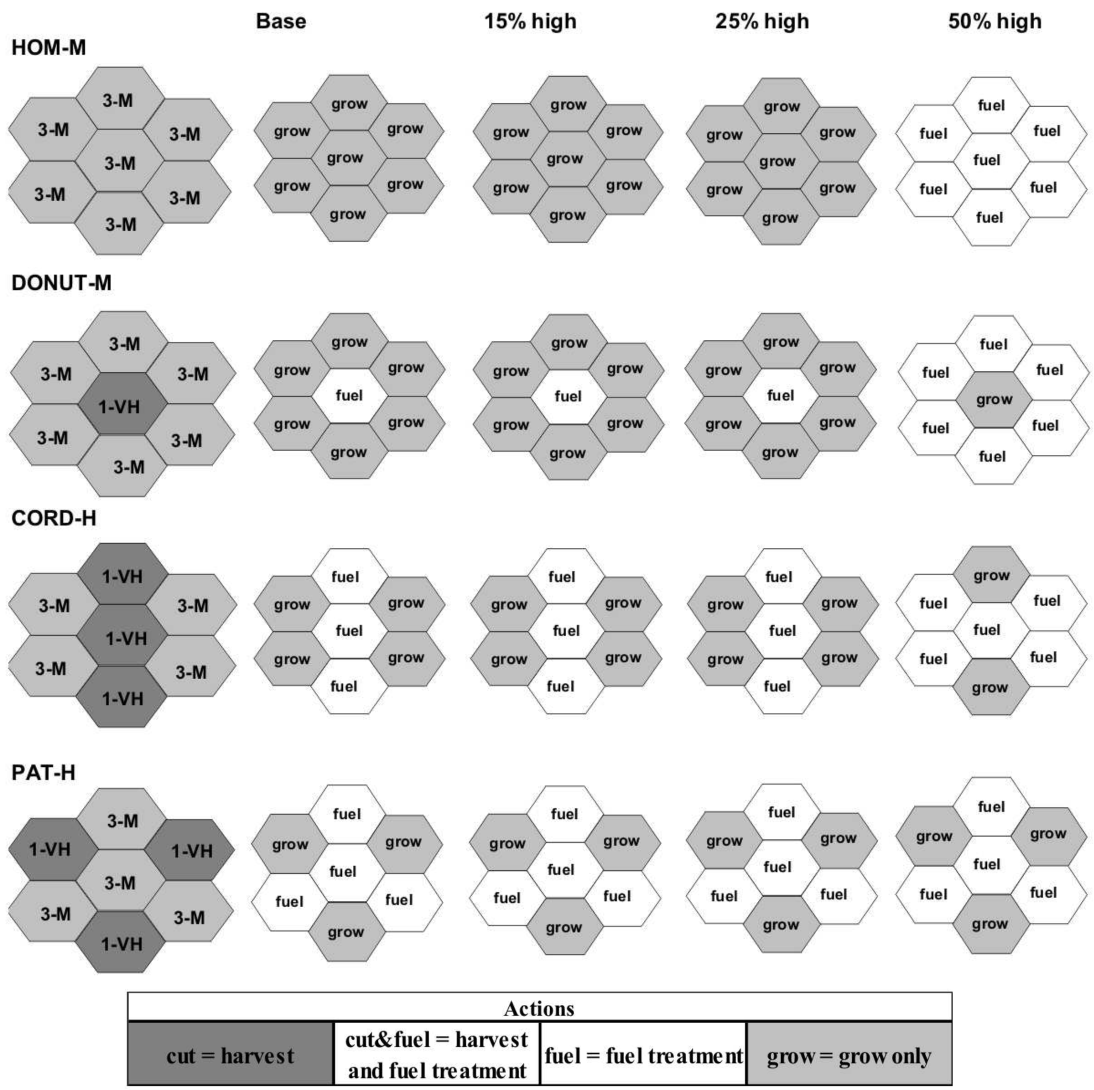


FIGURE 5.14: Optimal decisions for different high intensity levels of fuel treatments (labeled "action")

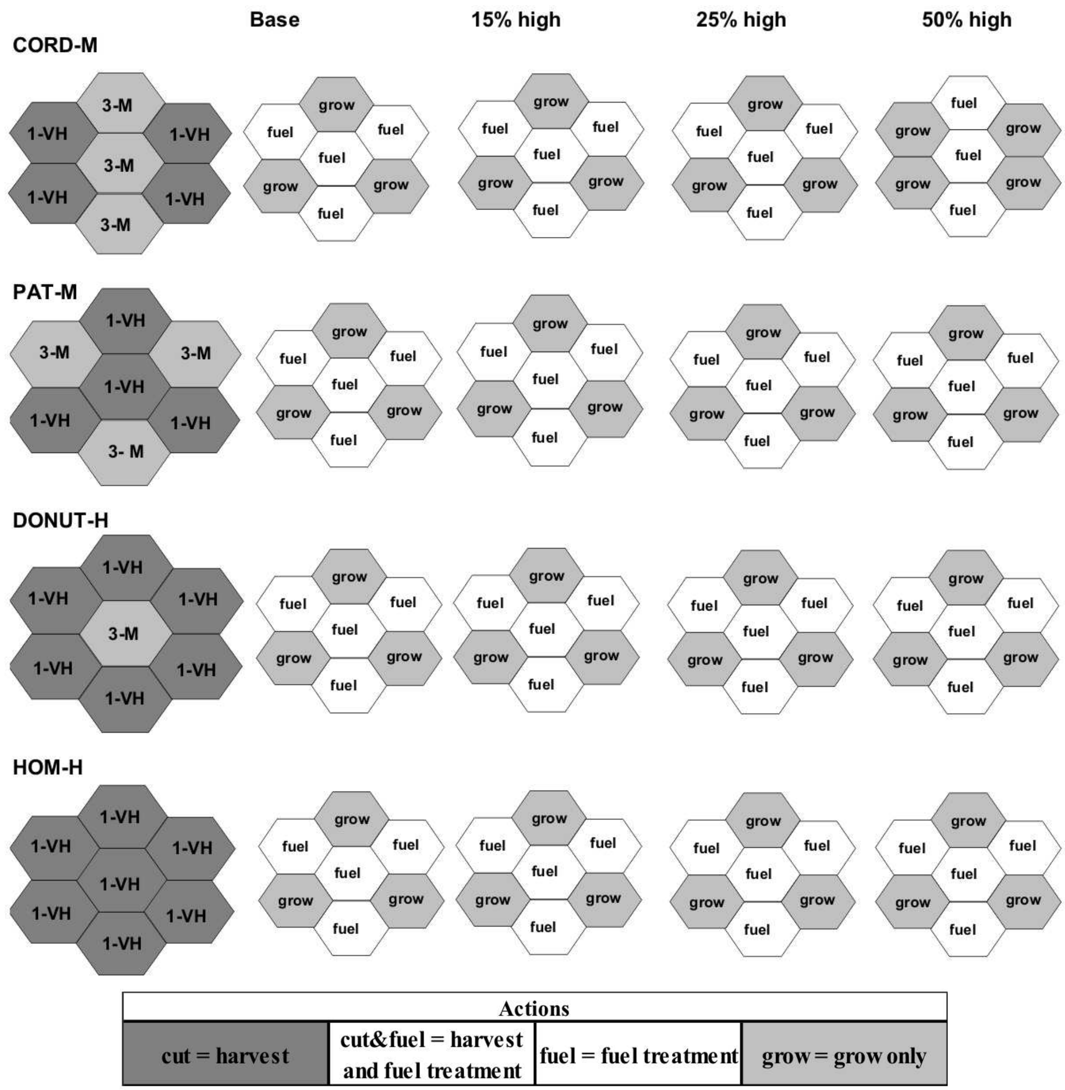
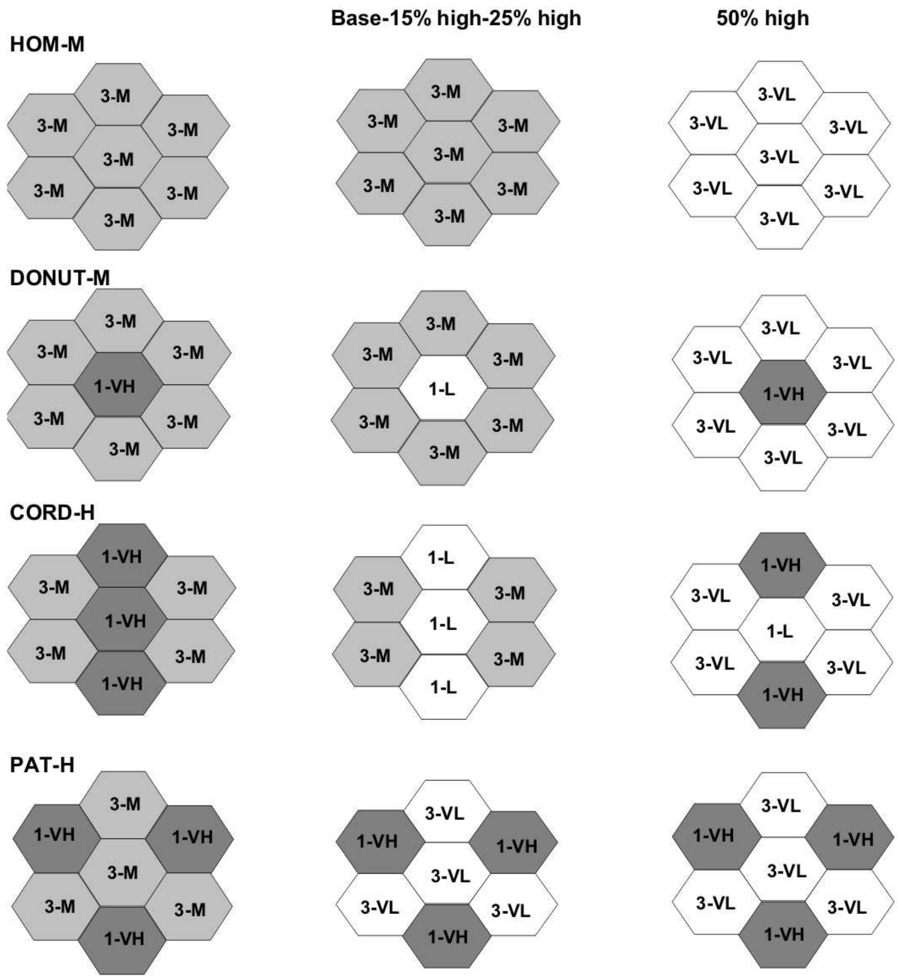


FIGURE 5.15: Optimal decisions for different high intensity levels of fuel treatments (labeled "action")



Fuel Condition Class				
VL = Very Low	L = Low	M = Medium	H = High	VH = Very High

FIGURE 5.16: Optimal landscapes for different high intensity levels of fuel treatments after optimal decision is applied (labeled "age class - fuel condition")

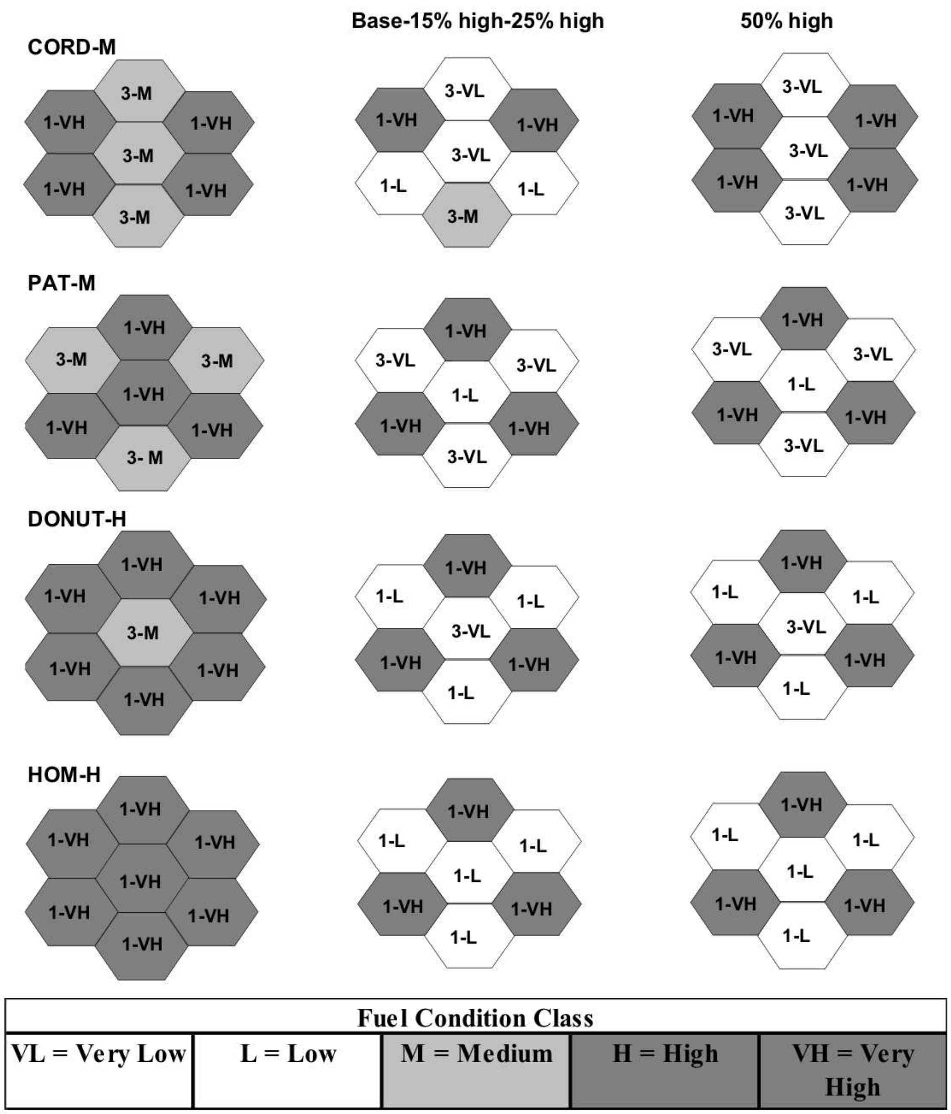


FIGURE 5.17: Optimal landscapes for different high intensity levels of fuel treatments after optimal decision is applied (labeled "age class - fuel condition")

5.2.2. Weather Frequency

Weather conditions during fire events partially determine the spread of fire because weather conditions define fire durations. The base case uses the probability of 0.6 for mild weather condition occurrence and the probability of 0.4 for severe weather condition occurrence. The higher the probability of severe weather conditions, the higher the risk of value loss in multiple MUs is because under severe weather conditions fire spreads to multiple MUs due to long fire duration. On the other hand, the higher the probability of mild weather conditions, the lower the risk of large fire damage is because under mild weather, fire will not spread over multiple MUs due to short fire duration. I evaluate how the optimal decision varies if one of these weather conditions occurs more frequently than the other. I evaluate two cases with high frequency severe weather conditions and two cases with high frequency mild weather conditions.

Mild Weather Frequency

I evaluate two cases where mild weather occurs with high frequency. In the first case, mild weather occurs with a probability of 0.8 (severe weather occurs with a probability of 0.2). In the second case, only mild weather occurs. When mild weather conditions occurs more frequently, it is less likely that an ignition burns multiple MUs. Under severe weather conditions, fire starting from an untreated MU of age class 1 burns not only the first layer adjacent MUs but also burns a second layer of MUs which are adjacent to the first layer of MUs. However, under mild weather conditions, fire starting from an untreated MU of age class 1 will burn only the first layer adjacent MUs. Figure 5.18 and Figure 5.19 depict how the optimal decision changes in accordance with different frequency of mild weather conditions. In the figures, the frequency of mild weather conditions increases from left to right. Figure 5.20 and Figure 5.21 depict how the optimal landscape changes in accordance with different frequency of mild weather conditions after the optimal decision is applied.

A land manager tends to treat more valuable MUs in landscapes. A land manager focuses his or her management efforts on valuable MUs because under mild weather conditions, the risk of value loss by the spread of fire is small and also because values gained from treating valuable MUs are larger than those from treating MUs with high spread rates, which have age class 1.

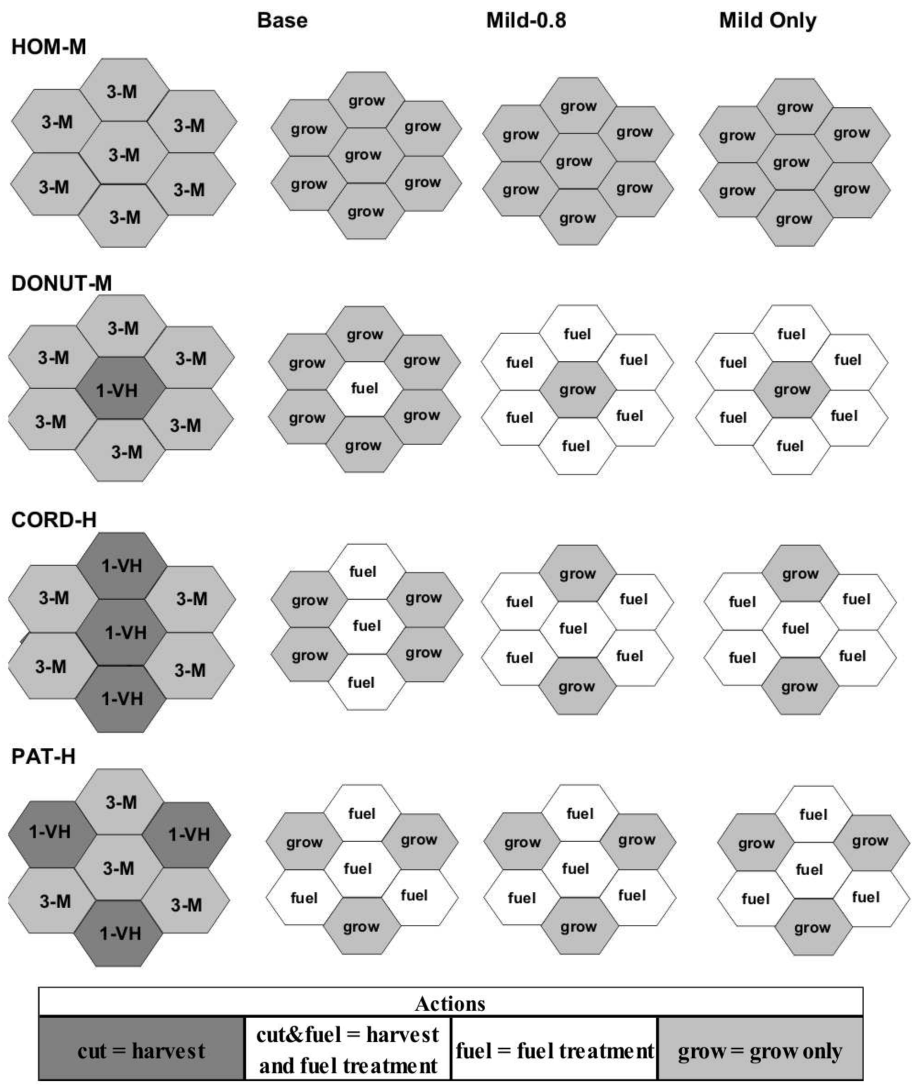


FIGURE 5.18: Optimal decisions for different frequency of mild weather conditions (labeled "actions")

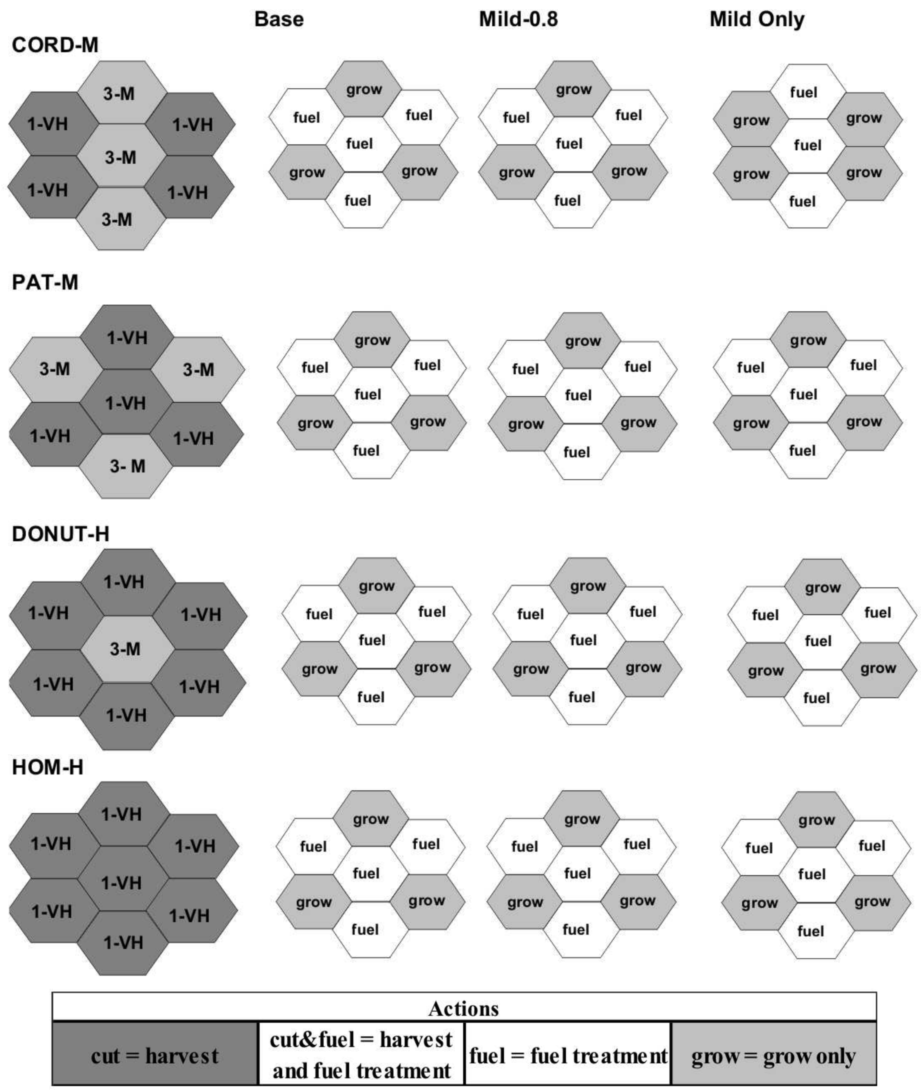
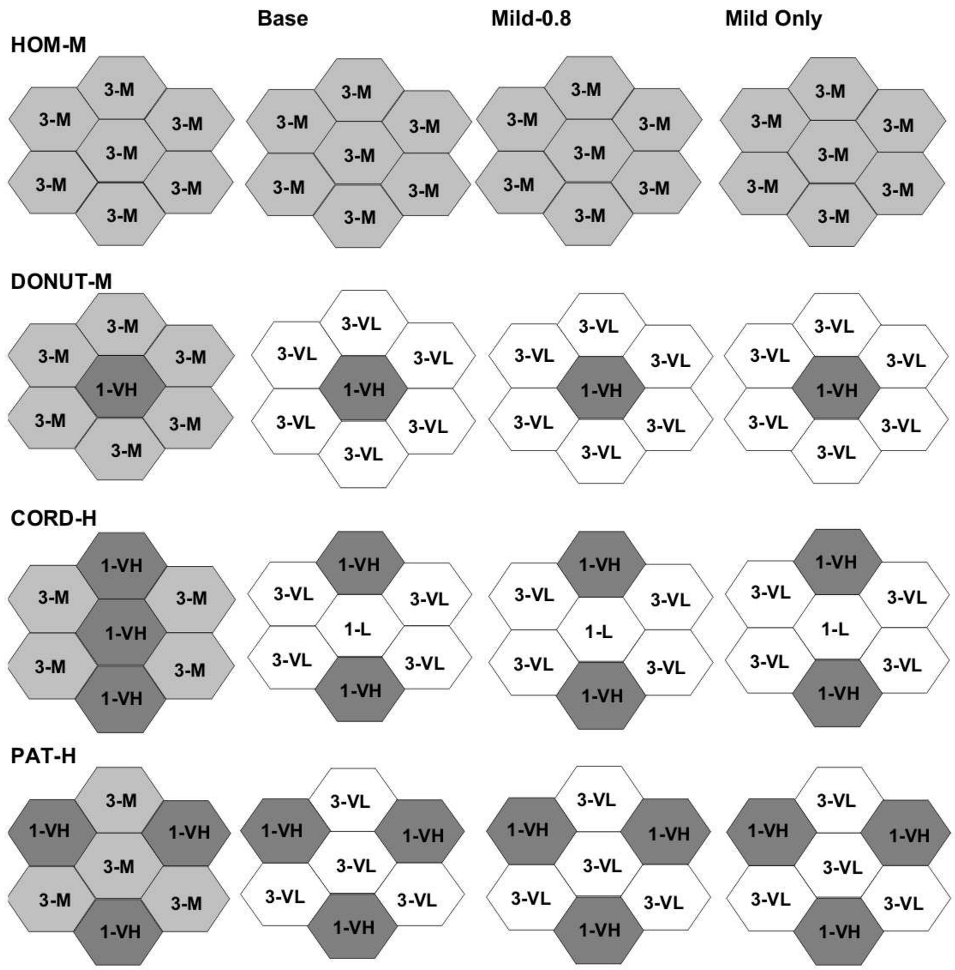


FIGURE 5.19: Optimal decisions for different frequency of mild weather conditions (labeled "actions")



Fuel Condition Class				
VL = Very Low	L = Low	M = Medium	H = High	VH = Very High

FIGURE 5.20: Optimal landscapes for different frequency of mild weather conditions after optimal decision is applied (labeled "age class - fuel condition")

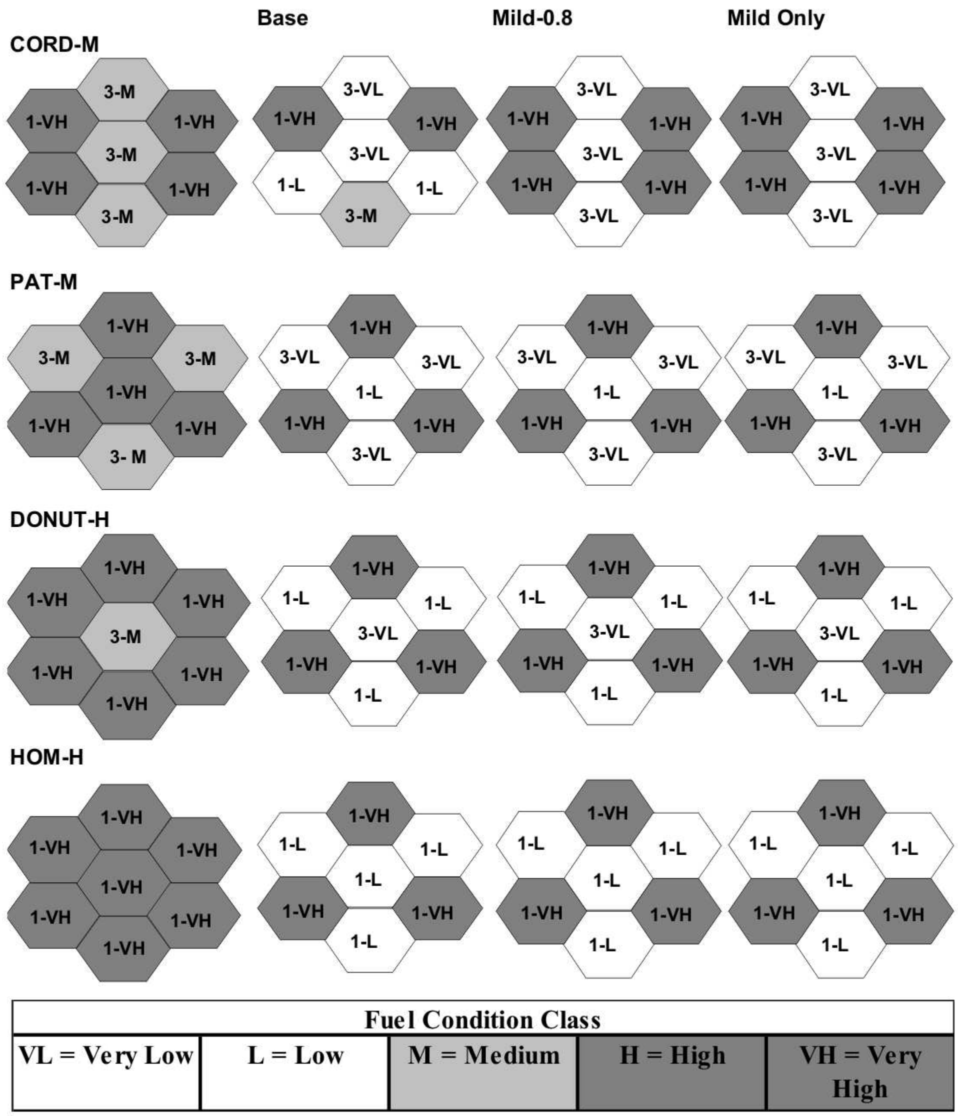


FIGURE 5.21: Optimal landscapes for different frequency of mild weather conditions after optimal decision is applied (labeled "age class - fuel condition")

High Severe Weather Frequency

I evaluate two cases where severe weather occurs with high frequency. In the first case, severe weather occurs with a probability of 0.8 (mild weather occurs with a probability of 0.2). In the second case only severe weather occurs. When severe weather conditions occur more frequently, it is more likely that fire causes more damage by spreading over a larger area (i.e. multiple MUs). Because fire starting from an untreated MU of age class 3 does not burn adjacent MUs under either mild or severe weather conditions, the probability of fire that spreads from untreated MUs of age class 3 to adjacent MUs is zero. Therefore, the spread of fire is not an issue in the landscape consisting of untreated MUs of age class 3. However, fire that starts from an untreated MU of age class 1 spreads to adjacent MUs under severe weather conditions. The risk of fire damage in each MU increases when severe weather conditions occur more frequently, if the landscape contains untreated MUs of age class 1. Figure 5.22 and Figure 5.23 depict how the optimal decision changes in accordance with different frequencies of severe weather conditions. In the figures, the frequency of severe weather conditions increases from left to right. Figure 5.24 and Figure 5.25 depict how the optimal landscape changes in accordance with different frequencies of severe weather conditions after the optimal decision is applied.

A land manager treats all MUs of age class 1 and leaves MUs of age class 3 untreated (Figure 5.22 and Figure 5.23). Under severe weather conditions, a land manager tends to focus his or her effort on protecting the landscape from the spread of fire. A land manager has more incentive to treat MUs with very high spread rates because leaving MUs with very high spread rates untreated increases the risk of value loss in multiple MUs when severe weather conditions occur frequently.

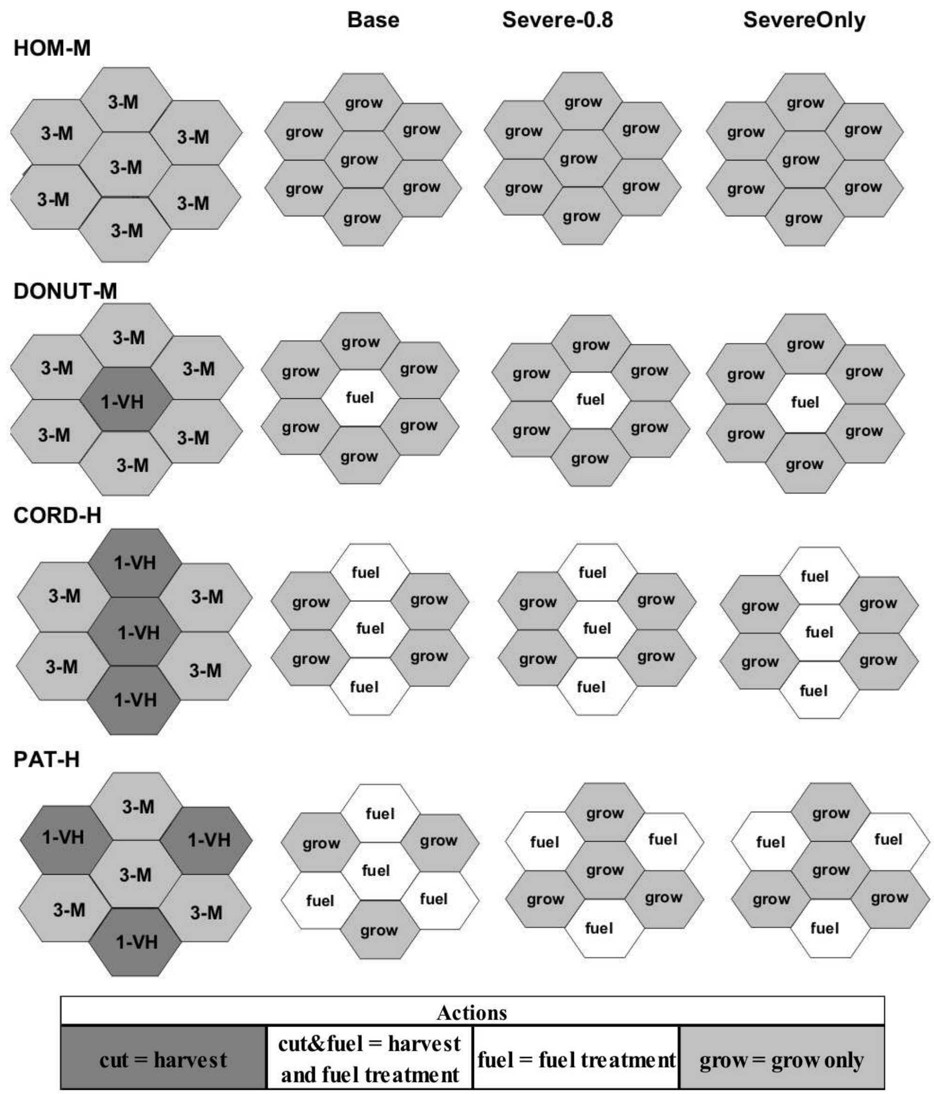


FIGURE 5.22: Optimal decision for different frequency of severe weather conditions (labeled "action")

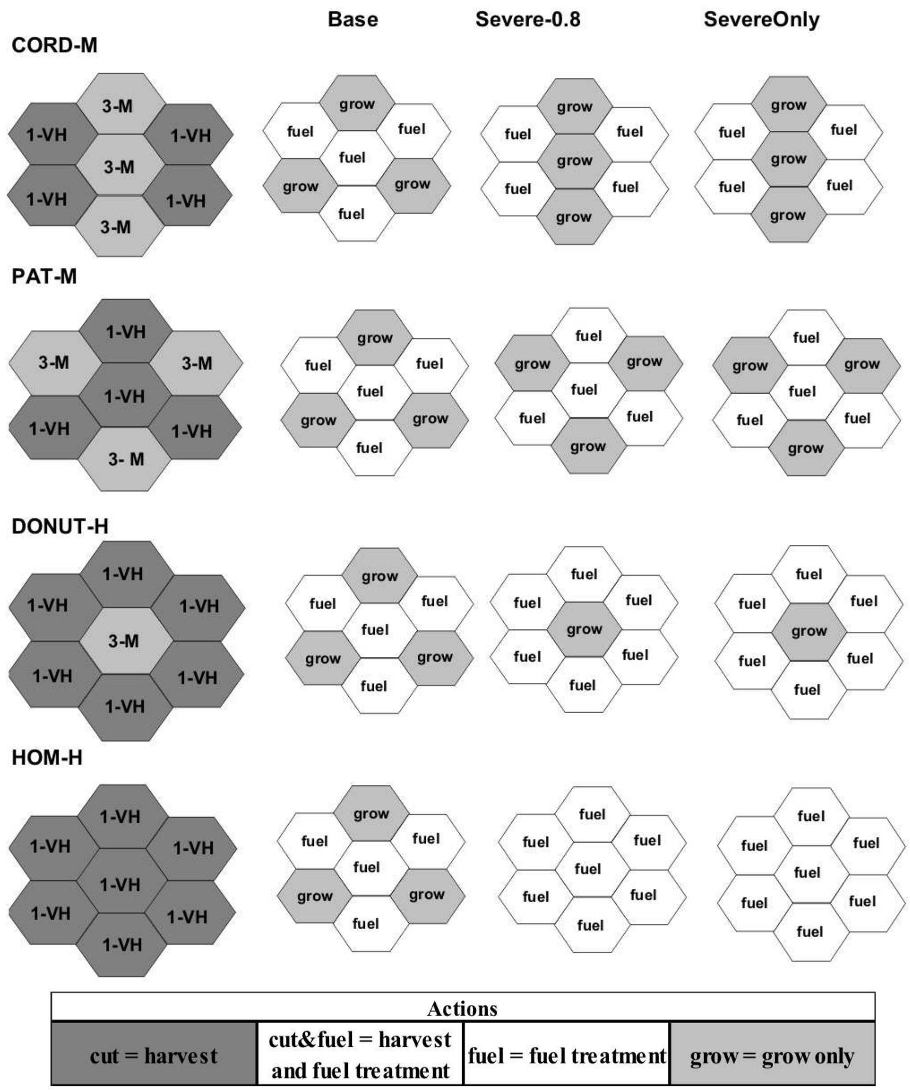


FIGURE 5.23: Optimal decision for different frequency of severe weather conditions (labeled "action")

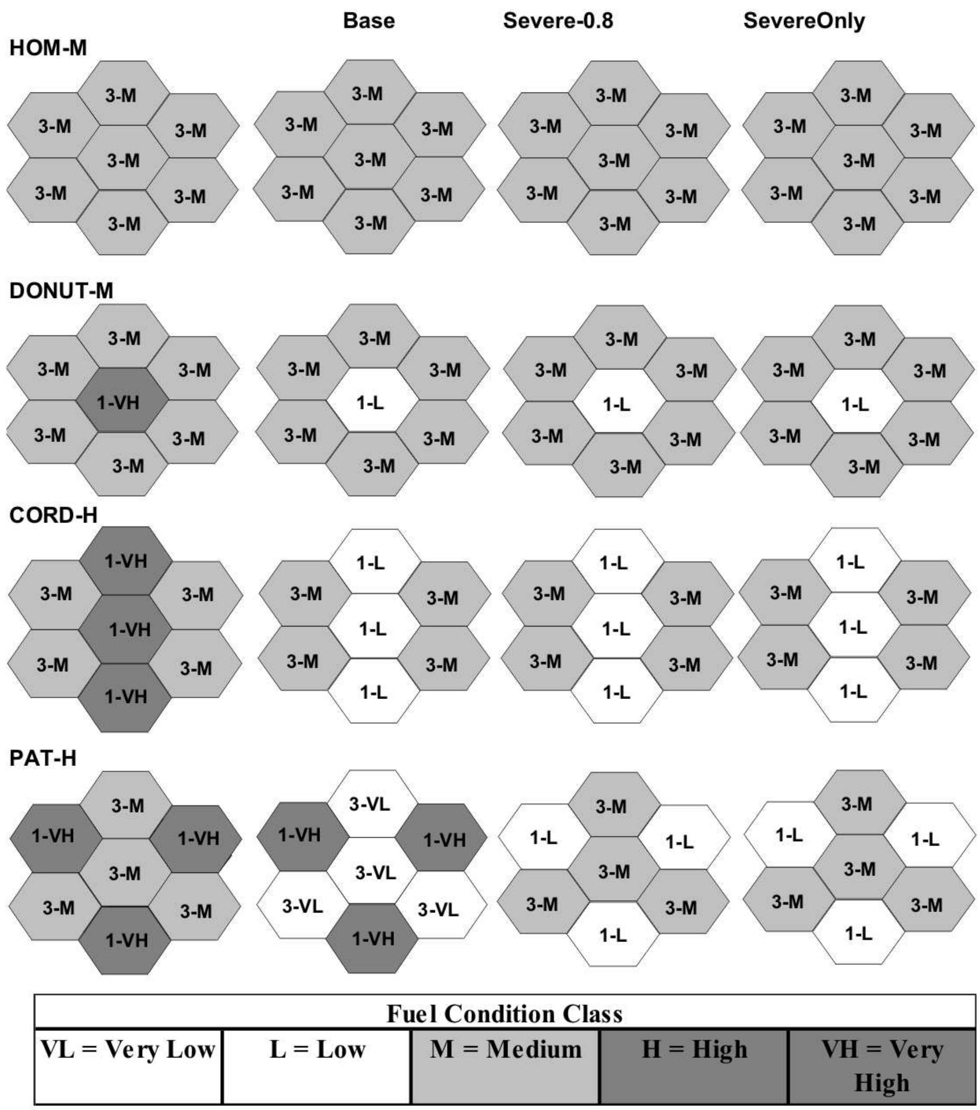
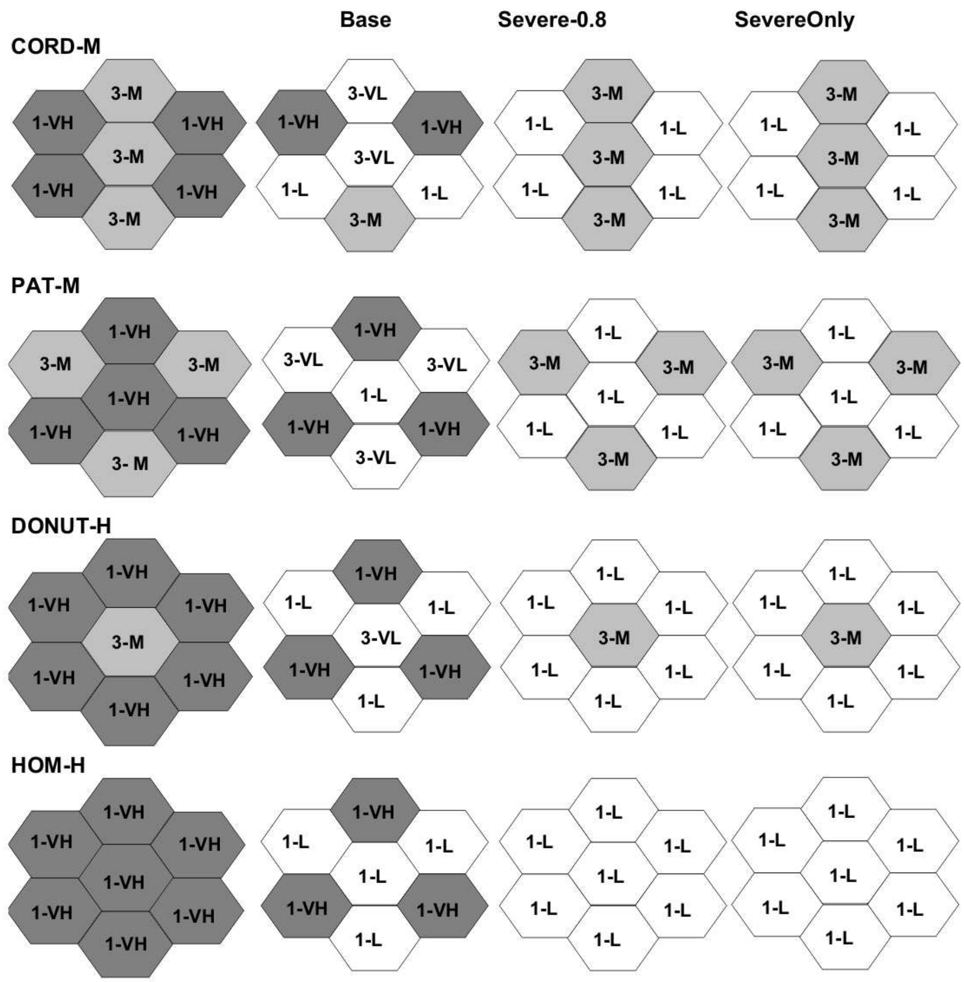


FIGURE 5.24: Optimal landscapes for different frequency of severe weather conditions after optimal decision is applied (labeled "age class - fuel condition")



Fuel Condition Class				
VL = Very Low	**L = Low**	**M = Medium**	**H = High**	**VH = Very High**

FIGURE 5.25: Optimal landscapes for different frequency of severe weather conditions after optimal decision is applied (labeled "age class - fuel condition")

5.2.3. Fire Frequency

In the base case, each MU has an ignition probability of 0.2 over a decade. Based on this assumption, the probability of each fire pattern is generated. When each fire pattern occurs more (less) frequently, the risk of fire damage in each MU will increase (decrease). I evaluate how the optimal decision varies when each fire pattern occurs more (less) frequently.

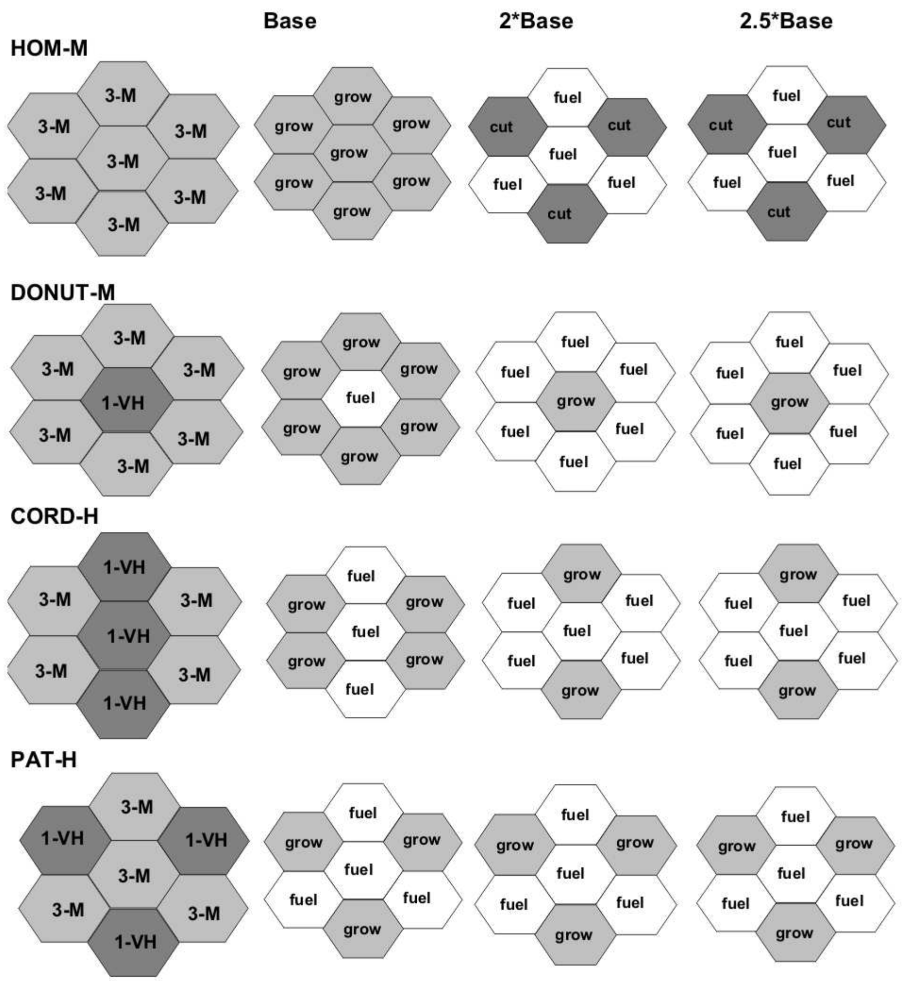
High Fire Frequency

I evaluate two high fire occurrence levels, one where the frequency is double the base case and the other where the frequency is 2.5 times the base case. Figure 5.26 and Figure 5.27 depict how the optimal decision changes in accordance with different fire frequency levels. In the figures, the level of fire frequency increases from left to right. Figure 5.28 and Figure 5.29 depict how the optimal landscape changes in accordance with different fire frequency levels.

A land manager treats more MUs of age class 3 compared with base case when fire occurs frequently (Figure 5.26 and Figure 5.27). Treating these valuable MUs is attractive because when fire occurs frequently and, therefore, the risk of fire damage in each MU is high, a land manager increases revenues more by protecting and reducing the risk of fire damage on valuable MUs. In other words, not protecting these valuable MUs lowers the discounted expected revenue significantly. Therefore, protection of on-site value will be a dominant decision when fire occurs frequently.

For the base case, in landscape, HOM-M, which is fully covered with valuable MUs of age class 3, the optimal decision is not to treat at all but to grow MUs to the 2nd period (Figure 5.26). For the base case, leaving MUs untreated is optimal because the risk of fire loss is low enough so that any treatment is unnecessary. However, when fire occurs more frequently, a land manager decides to harvest some valuable MUs during the current period (Figure 5.26). Harvesting becomes attractive because the risk of value loss in each MU becomes high and, becomes too risky to hold timber at the site.

In landscapes HOM-H and DONUT-H, a land manager treats all MUs with very high spread rates (Figure 5.27). For the base case, the optimal decision in these landscapes is to assign fuel treatment to four MUs and leave three MUs untreated (Figure 5.27). Treating all MUs is protecting the landscape too much so that an increase in the expected NPV, from fewer fuel treatment investment to more fuel treatment investment, is smaller than an increase in the cost (the marginal cost of fuel treatment exceeds the marginal increase in the expected NPV). However, when fire occurs more frequently, the risk of value loss in each MU is high. Therefore, a decrease in the expected NPV by leaving three MUs with very high spread rates untreated becomes larger than the treatment cost saved during the current period. Therefore, a land manager treats more MUs in landscapes HOM-M and DONUT-H when fire occurs more frequently.



Actions			
cut = harvest	cut&fuel = harvest and fuel treatment	fuel = fuel treatment	grow = grow only

FIGURE 5.26: Optimal decisions for different levels of high fire frequency (labeled "action")

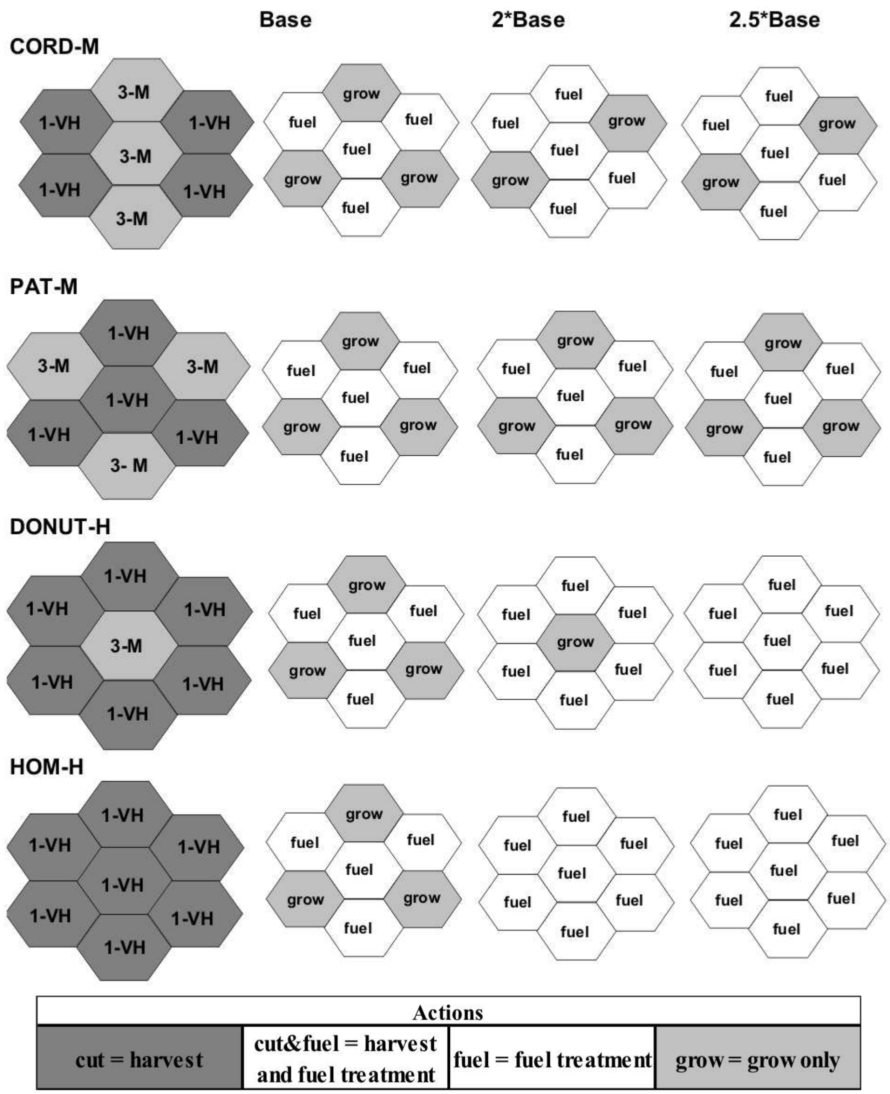
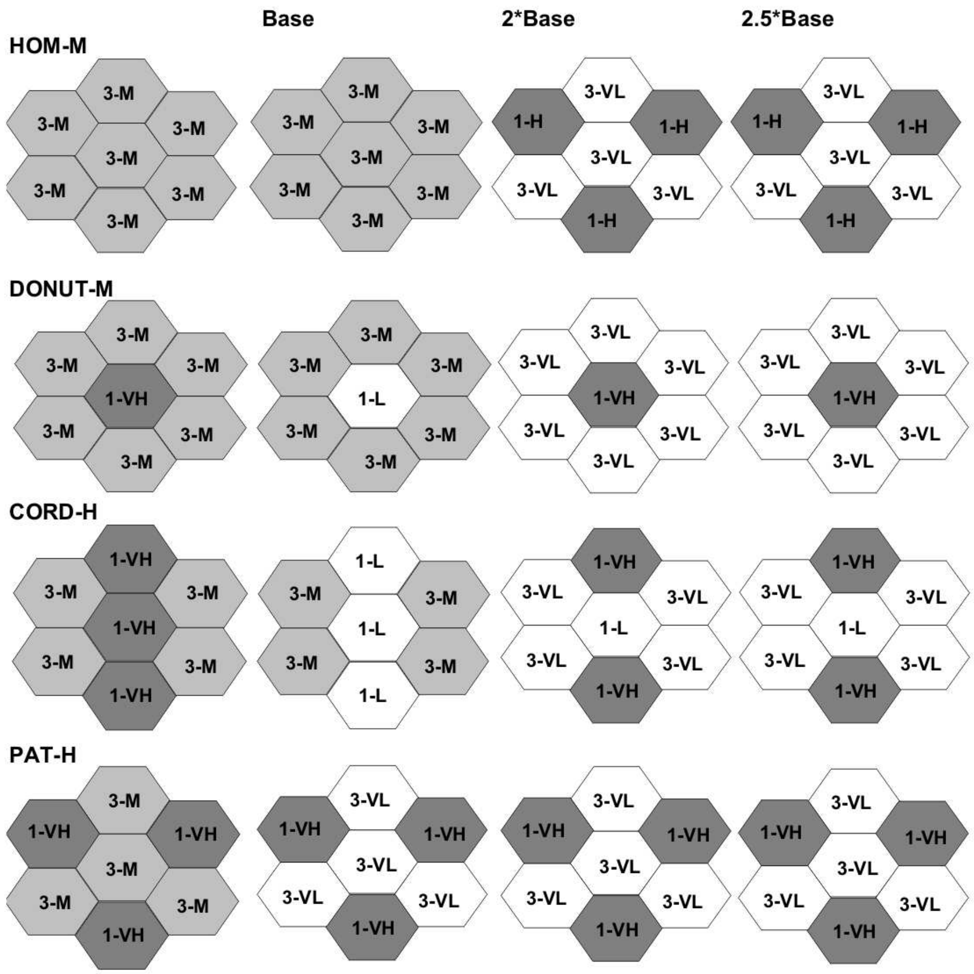
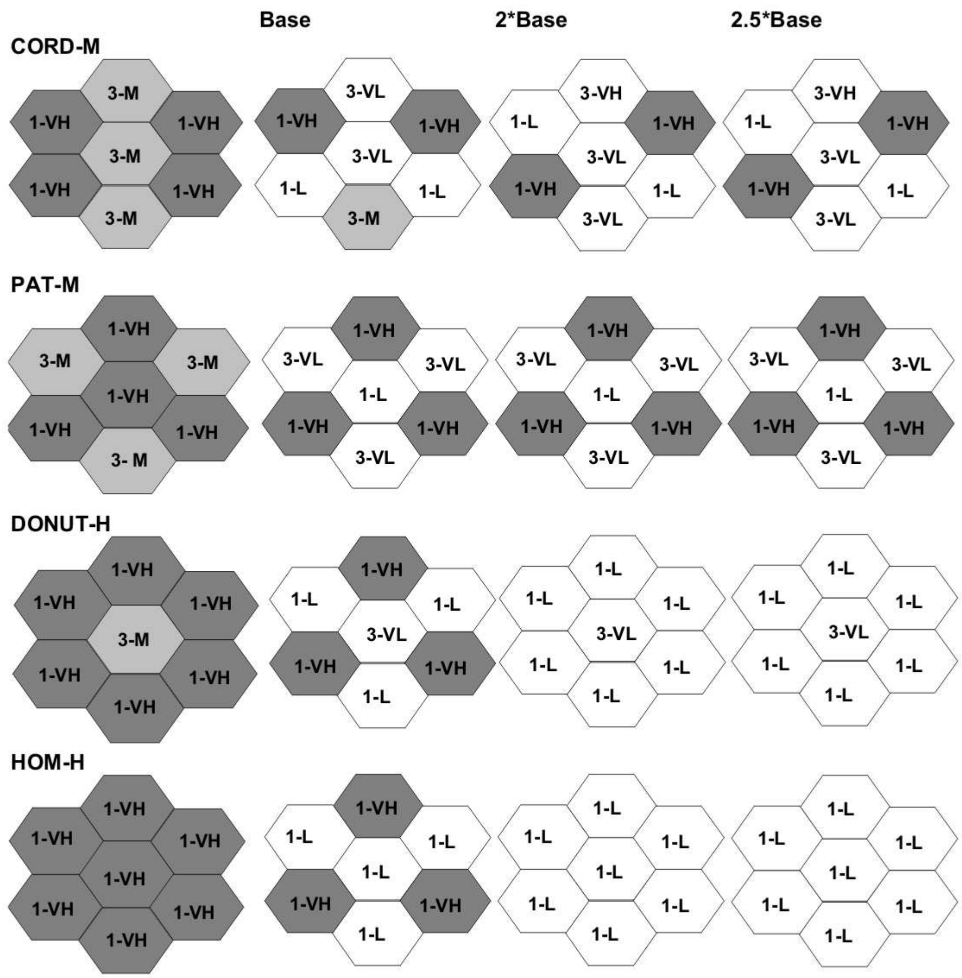


FIGURE 5.27: Optimal decisions for different levels of high fire frequency (labeled "action")



Fuel Condition Class				
VL = Very Low	L = Low	M = Medium	H = High	VH = Very High

FIGURE 5.28: Optimal landscapes for different levels of high fire frequency after optimal decision is applied (labeled "age class - fuel condition")



Fuel Condition Class				
VL = Very Low	L = Low	M = Medium	H = High	VH = Very High

FIGURE 5.29: Optimal landscapes for different levels of high fire frequency after optimal decision is applied (labeled "age class - fuel condition")

Low Fire Frequency

I evaluate two low fire occurrence levels, one where the frequency is half the base case and the other where the frequency is 0.25 times than the base case. At a lower probability of each fire pattern occurrence, the risk of fire loss in each MU is small. Therefore, the benefits from reducing the risk of fire loss through fuel treatment become smaller compared with the base case. Figure 5.30 and Figure 5.31 depict how the optimal decision changes in accordance with different fire frequency. In the figures, the level of fire frequency decreases from left to right. Figure 5.32 and Figure 5.33 depict how the optimal landscape changes in accordance with different fire frequencies after the optimal decision is applied.

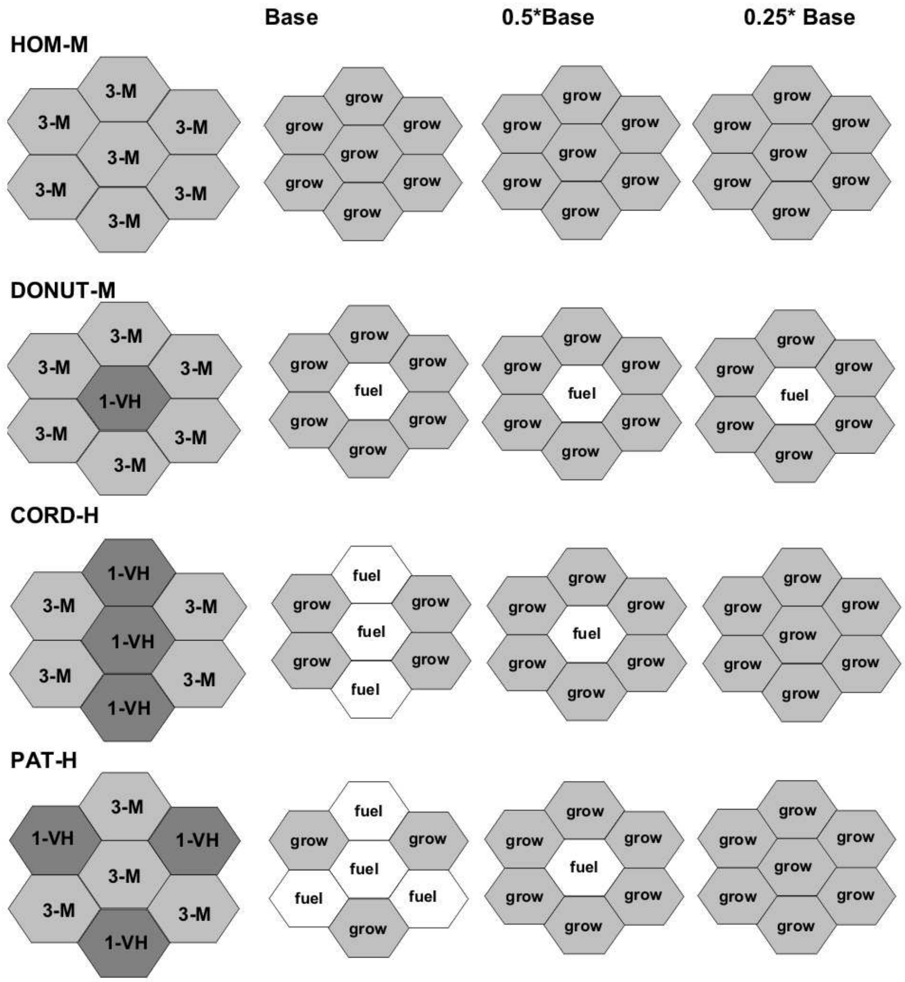
When the probability of each fire pattern occurrence is low at the level of half the base case, a land manager treats only the center MU in landscapes except DONUT-H (Figure 5.30 and Figure 5.31). Assigning fuel treatment to less MUs is optimal because the risk of value loss by fire damage is low. Protecting the center MU is important, for example, in landscape PAT-H, if none of MUs including the center MU is not treated, fire starting from the center MU burns all MU under severe weather conditions. However if the center MU is treated, fire starting from this center MU burns only itself under severe weather condition. Also, the ignition from one of MUs with very high spread rates in outer lanes burns the center MU, if it is not treated. However, if the center MU is treated, the center MU is not burned from the ignition from one of MUs with very high spread rates in outer lanes. Therefore, protecting the center MU reduces the risk of value loss in multiple MUs significantly.

Although when fire frequency is low protecting only the center MU is generally optimal, two MUs with very high spread rates in outer lanes are treated in landscape

DONUT-H (Figure 5.31). Treating two MUs in outer lanes is optimal because this landscape is covered by continuous MUs with high spread rates. Ignition from any MUs burns all MUs except the one which is located furthest from an ignition point. Treating two MUs with very high spread rates in the way so that continuous surrounding of MUs with high spread rate is disconnected (Figure 5.33) reduces the risk of fire loss in each MU significantly.

When each fire pattern probability is quarter as high as the base case, a land manager decides to assign no fuel treatment in all landscapes except landscape DONUT-M (Figure 5.30 and Figure 5.31). Treating no MUs is optimal because the risk of fire damage is too low and further decreasing the risk though treatments is too costly. The marginal cost of fuel treatment exceeds the marginal expected NPV.

In landscape DONUT-M, a land manager assigns no fuel treatment when each fire probability is 0.11 times as high as base case. In this landscape, a land manager treats the center MU at a lower fire frequency because the center MU has a very high spread rate and MUs with merchantable timber (valuable) surround this "high-risk MU". If a land manager leaves this MU untreated, the expected NPV decreases significantly. Therefore, no treatment is not optimal in this landscape when fire frequency is 0.25 times than the base case .



Actions			
cut = harvest	cut&fuel = harvest and fuel treatment	fuel = fuel treatment	grow = grow only

FIGURE 5.30: Optimal decisions for different levels of low fire frequency (labeled "action")

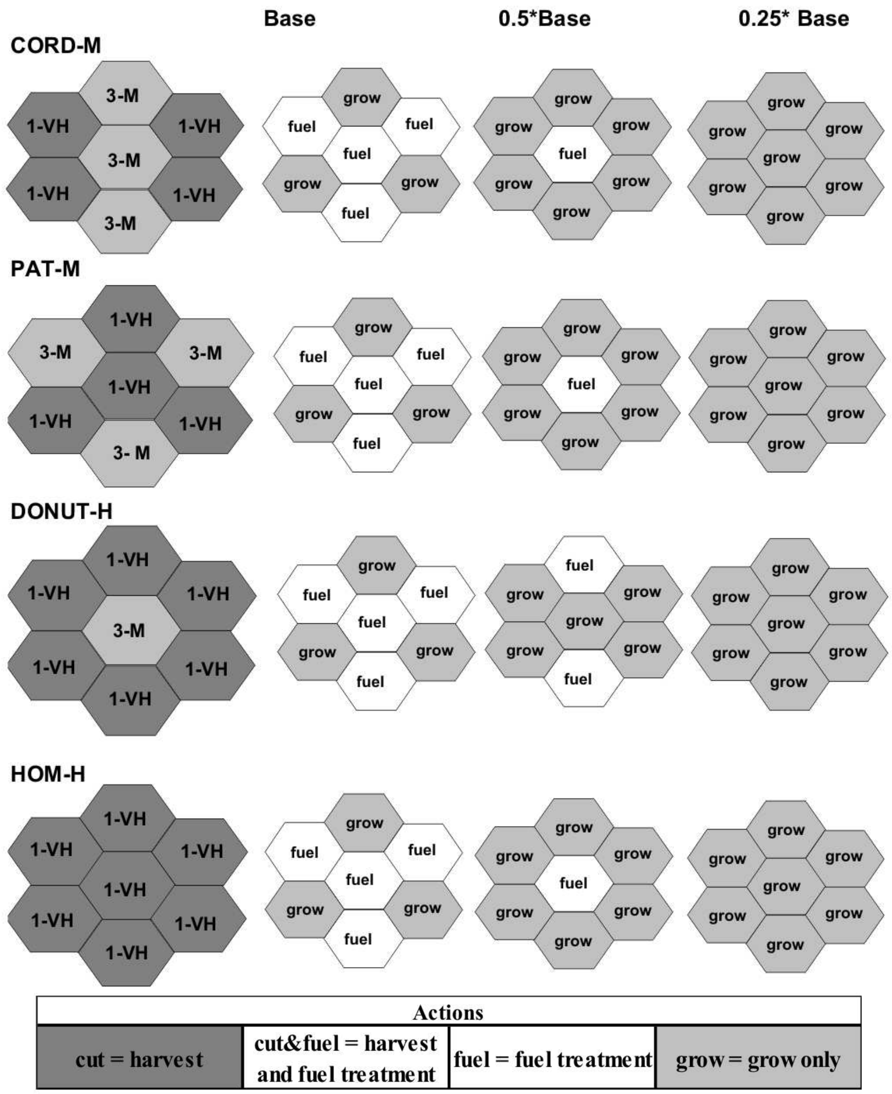
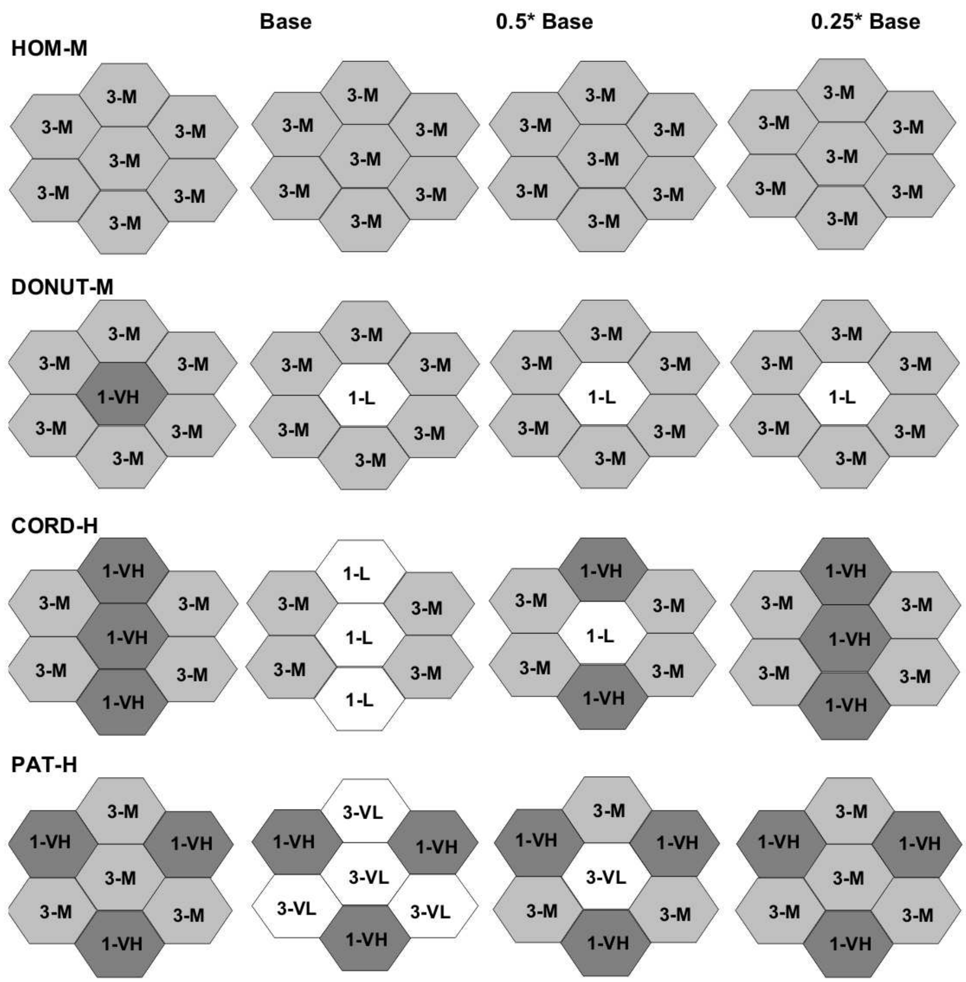
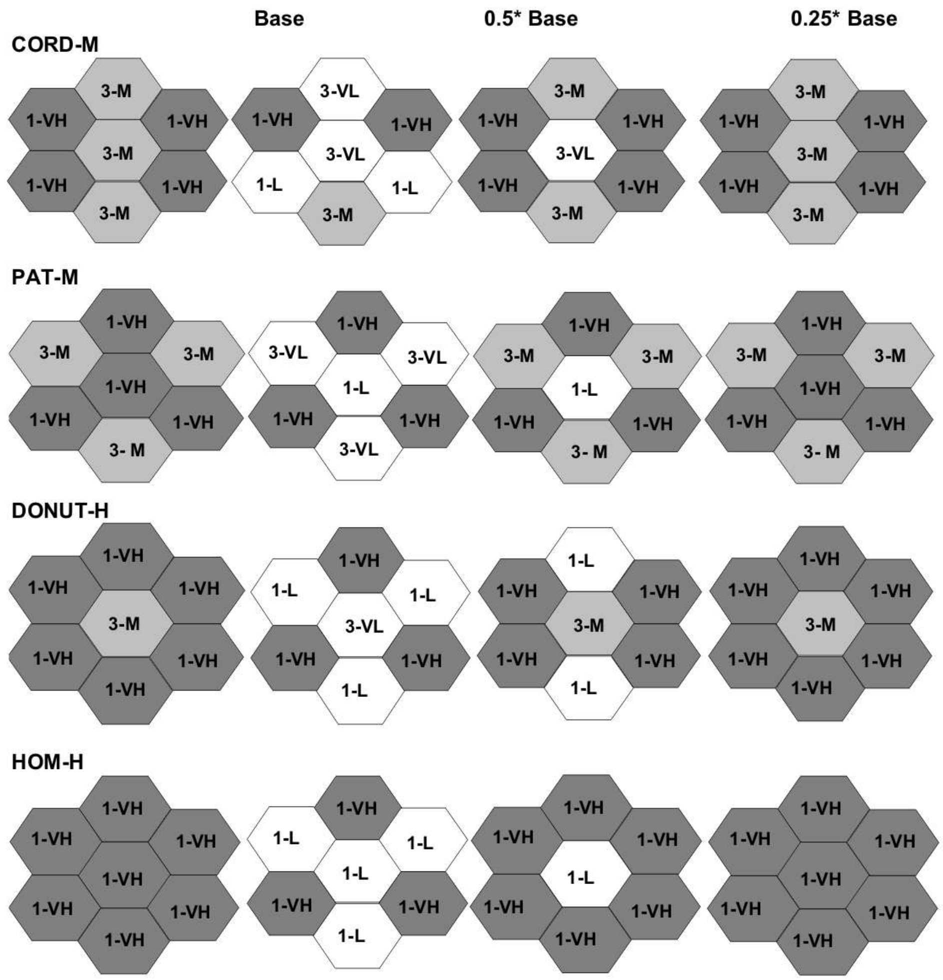


FIGURE 5.31: Optimal decisions for different levels of low fire frequency (labeled "action")



Fuel Condition Class				
VL = Very Low	L = Low	M = Medium	H = High	VH = Very High

FIGURE 5.32: Optimal landscapes for different levels of low fire frequency after optimal decision is applied (labeled "age class - fuel condition")



Fuel Condition Class				
VL = Very Low	L = Low	M = Medium	H = High	VH = Very High

FIGURE 5.33: Optimal landscapes for different levels of low fire frequency after optimal decision is applied (labeled "age class - fuel condition")

5.2.4. Fire Duration Time

The base case uses fire duration of 48 hours for mild weather conditions and fire duration of 96 hours for severe weather conditions. The longer the fire duration is, the larger an area will be burned. The shorter the fire duration is, the smaller an area will be burned. Therefore, the risk of value loss in multiple MUs increases as fire duration gets longer. I evaluated two cases of long fire duration and two cases of short fire duration in order to evaluate how the optimal decision varies with various fire durations.

Shorter Fire Duration Time

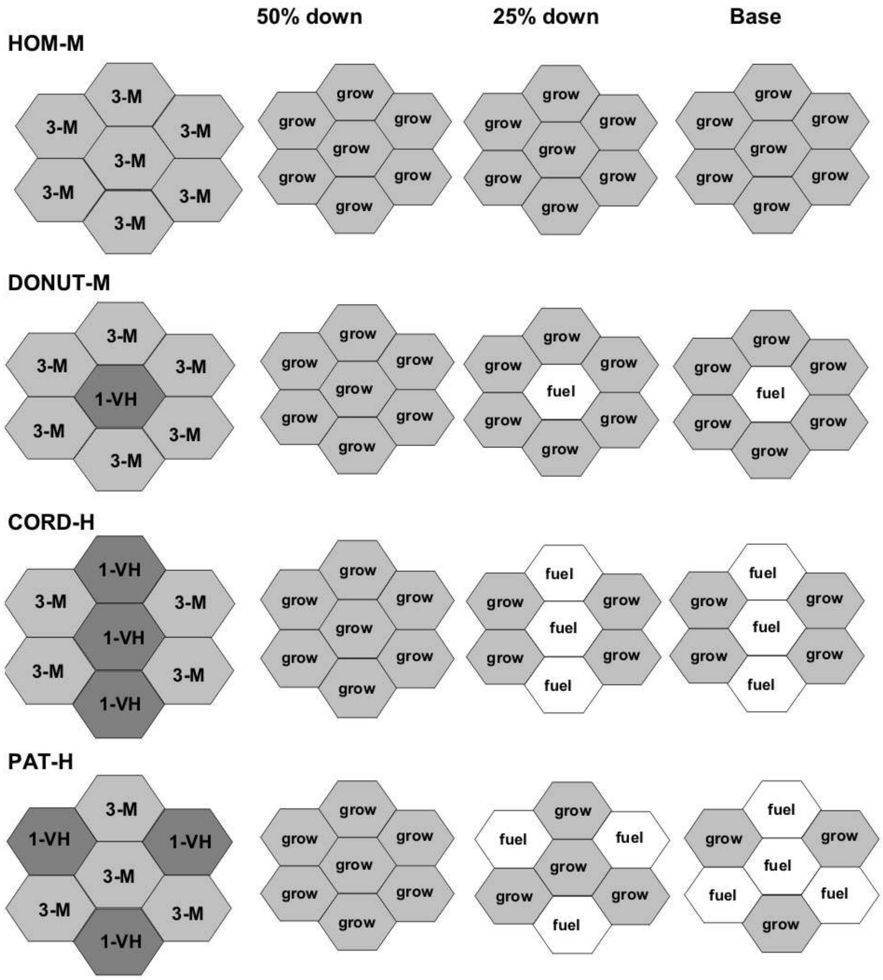
I evaluate two cases of short fire duration. One where duration time is 25% less than the base case (hereafter denoted as "short-T-25") and one where it is 50% less than the base case (hereafter denoted as "short-T-50"). For short-T-50, if MUs of age class 3 are treated, they are not burned under either severe or mild weather conditions. Therefore, the risk of value loss in these MUs is zero. Untreated MUs of age class 3 are burned only under severe weather condition, if they ignite, but fire does not spread to the adjacent MUs. If MUs of age class 1 are treated, they are burned only under severe weather condition. Untreated MUs of age class 1 are burned under either severe or mild weather conditions. When untreated MUs of age class 1 are connected with each other, if one of them ignites, fire spreads to its adjacent MUs of the same fuel conditions under severe weather condition.

For short-T-25, untreated MUs of age class 3 are burned only under severe weather condition, if they ignite but, fire does not spread to adjacent MUs. However, in the base case, these MUs are burned under either severe or mild weather conditions but, fire does not spread to the adjacent MUs of the same fuel conditions under either severe or mild weather conditions. For short-T-25, treated MUs of age class 1 are burned only under severe weather condition but, fire does not spread to adjacent MUs. However, in the base case, these MUs are burned under either mild or severe weather conditions but, fire does not spread to adjacent MUs. For short-T-25, untreated MUs of age class 1 are burned only themselves under mild weather condition and, fire spreads to the adjacent MU only under severe weather condition. Figure 5.34 and Figure 5.35 depict how the optimal decision changes in accordance with different fire durations. In the figures, fire duration increases from left to right. Figure 5.36 and Figure 5.37 depict how the optimal landscape changes in accordance with different fire durations after the optimal decision is applied.

A land manager assigns no fuel treatments in landscapes except PAT-M and HOM-H for short-T50 (Figure 5.34 and Figure 5.35). No treatment is optimal because the risk of fire damage in each MU is low due to extremely short fire duration under both possible weather conditions. The marginal cost of fuel treatment exceeds the marginal expected NPV. Therefore, further reducing the risk at a cost of $200/acre is not worth doing.

In landscapes PAT-M and HOM-H, a land manager treats only the center MU (Figure 5.35). Compared to the other landscapes, leaving the center MU untreated increases the risk of value loss in multiple MUs because MUs with very high spread rates are connected with each other and distributed over the landscape. Therefore, treating the center MU will reduce the risk of value loss by fire damage sufficiently enough in each MU to offset the cost of doing so. The marginal expected NPV exceeds the marginal cost of fuel treatment.

For short-T-25, the optimal decision generally yields a landscape which only consists of treated MUs of age class 1 and untreated MUs of age class 3 except landscapes DONUT-H and HOM-H (Figure 5.36 and Figure 5.37). Because of shorter fire duration time, fire starting from untreated MUs of age class 3 burns only themselves under severe weather condition. Therefore, leaving MUs of age class 3 untreated does not increase the risk of fire loss in each MU, if they are surrounded by treated MUs, which have fuel conditions of slower spread rates than those of MUs of age class 3. Therefore, the decision of leaving MUs of age class 3 untreated becomes optimal, while it might not be so for the base case. A land manager can focus his or her management effort on treating MUs with very high spread rates.



Actions			
cut = harvest	cut&fuel = harvest and fuel treatment	fuel = fuel treatment	grow = grow only

FIGURE 5.34: Optimal decisions for different short fire durations (labeled "action")

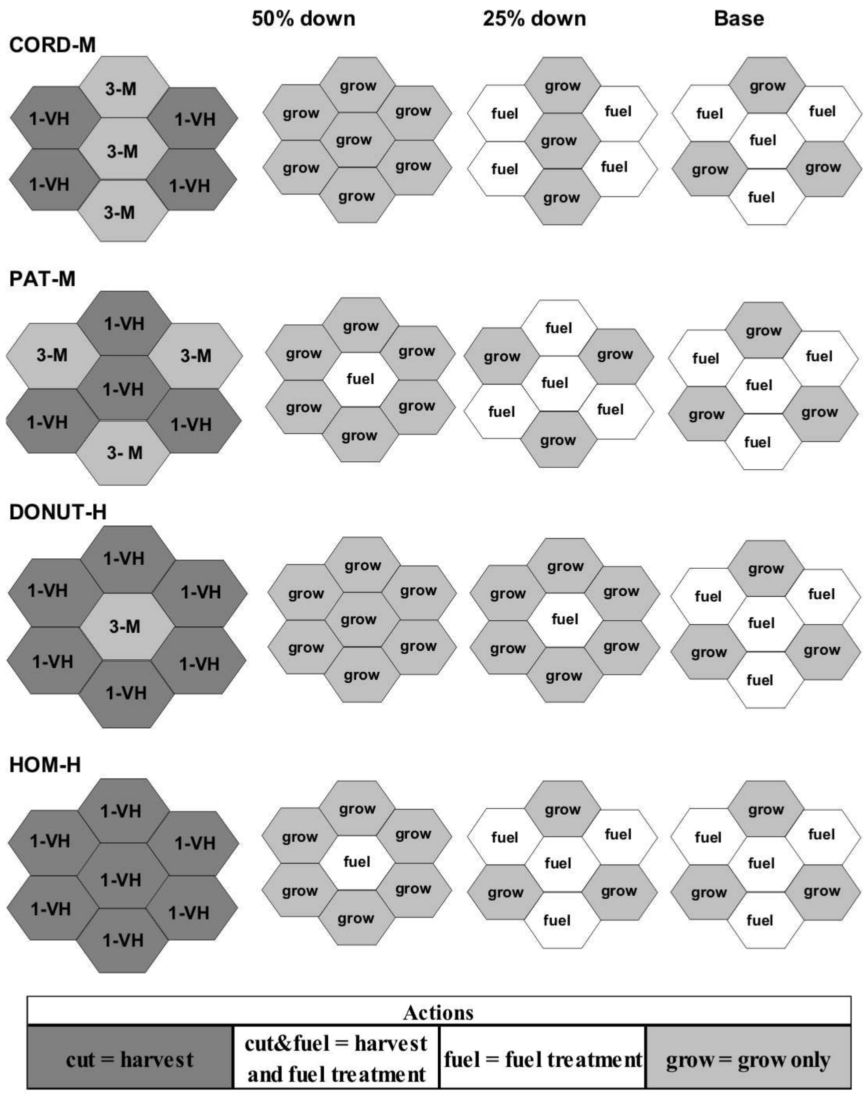
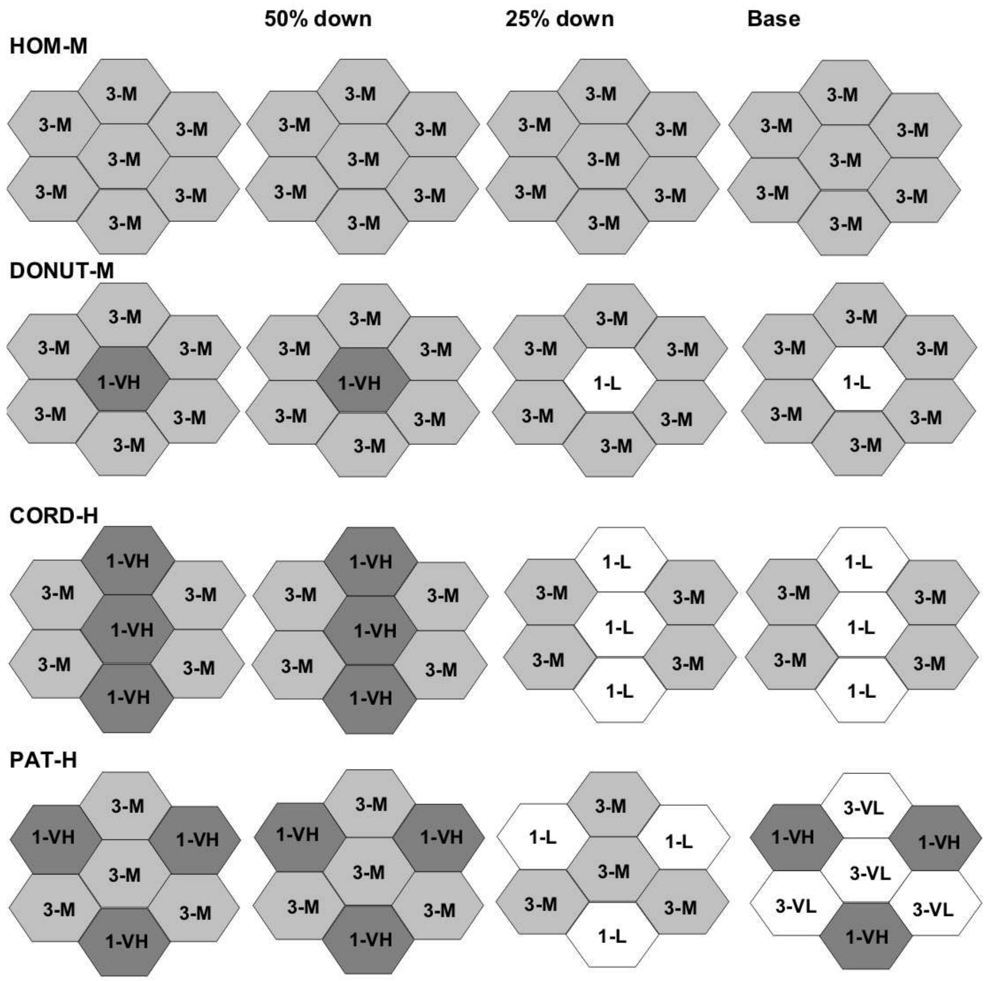
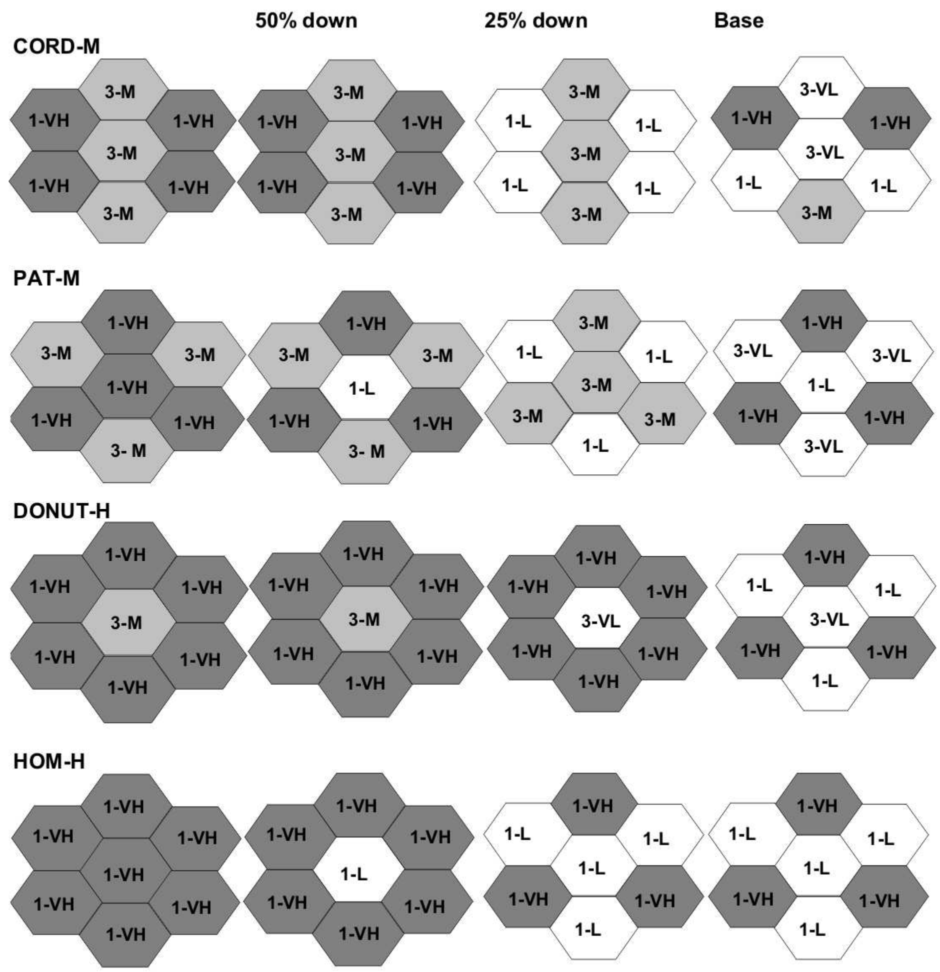


FIGURE 5.35: Optimal decisions for different short fire durations (labeled "action")



Fuel Condition Class				
VL = Very Low	L = Low	M = Medium	H = High	VH = Very High

FIGURE 5.36: Optimal landscapes for different short fire durations after optimal decision is applied (labeled "age class - fuel condition")



Fuel Condition Class				
VL = Very Low	L = Low	M = Medium	H = High	VH = Very High

FIGURE 5.37: Optimal landscapes for different short fire durations after optimal decision is applied (labeled "age class - fuel condition")

Longer Fire Duration Time

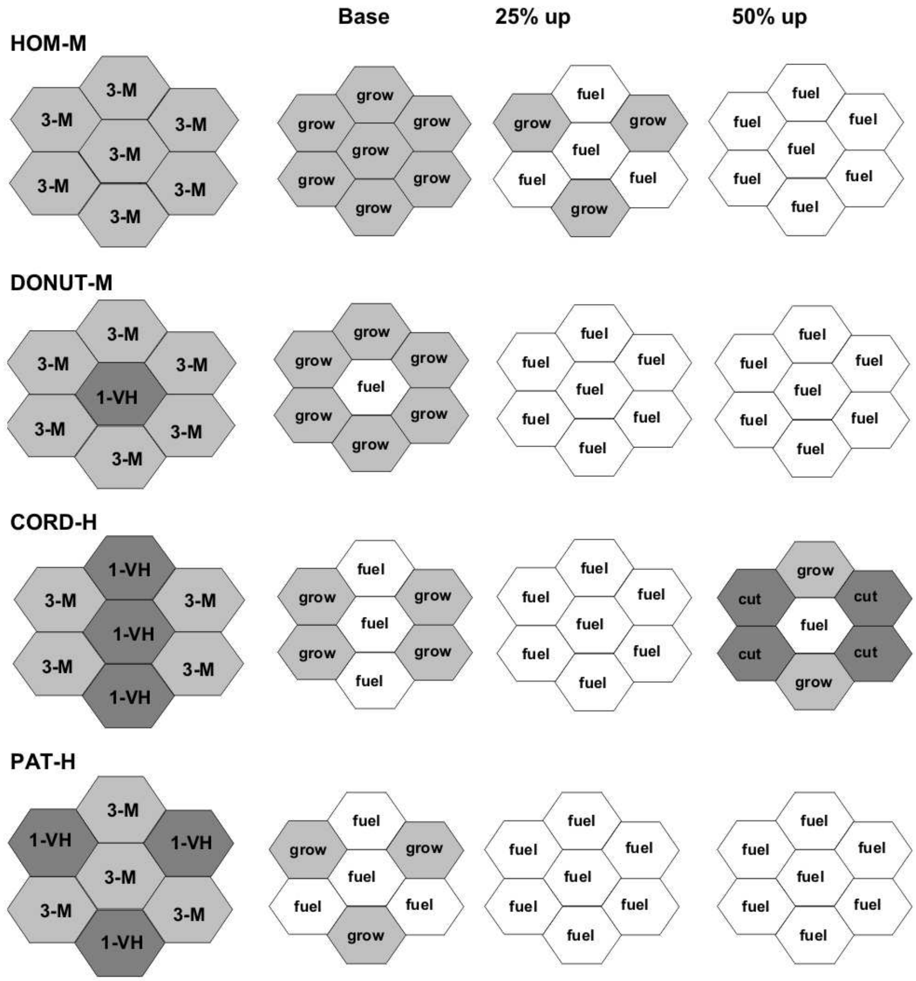
I also evaluate two cases of long fire duration. One is where the duration time is 25% more than the base case (hereafter denoted as "long-T-25") and one where it is 50% more than the base case (hereafter denoted as "long-T-50"). For long-T-25, if MUs of age class 3 are treated, they are burned only under severe weather condition, if they ignite. Under severe weather condition, fire starting from untreated MUs of age class 3 spreads to adjacent MUs of untreated MUs of age class 3. Under mild weather condition, fire that ignites from untreated MUs of age class 3 burns only themselves. For the base case, even under severe weather condition, fire starting from untreated MUs of age class 3 does not burn adjacent MUs.

For long-T-25, if MUs of age class 1 are treated, then they are burned, but fire does not spread to adjacent MUs under either severe or mild weather conditions. If untreated MUs of age class 1 ignite, fire spreads into the adjacent MUs of the same fuel condition under mild weather condition. Under severe weather condition, fire that ignites from untreated MUs of age class 1 spreads into the next two adjacent MUs (not only to their adjacent MUs but also to the adjacent MUs of the adjacent MUs see Figure). These fire growth patterns are the same as the base case.

For long-T-50, if MUs of age class 3 are treated, they are burned under either severe or mild weather conditions, but fire does not spread to adjacent MUs. If untreated MUs of age class 3 ignite, fire spreads into the adjacent MUs under severe weather condition, however, fire that ignites from untreated MUs of age class 3 does not spread to adjacent MUs under mild weather condition. Under severe weather condition, if treated MUs of age class 1 are next to each other and fire ignites from one of these MUs, the adjacent treated MUs of age class 1 is also burned. However, for long-T-25, under either severe or mild weather conditions, if treated MUs of age class 1 are next to each other, then fire starting from one of these MUs burns only themselves but fire does not spread to adjacent MUs. For long-T-50, if untreated MUs of age class 1 ignite, then fire spreads into adjacent MUs under mild weather condition. Under severe weather condition if untreated MUs of age class 1 ignite, fire spreads to the next two adjacent MUs. Figure 5.38 and Figure 5.39 depict how the optimal decision changes in accordance with different fire durations. In the figures, fire duration increases from left to right. Figure 5.40 and Figure 5.41 depict how the optimal landscape changes in accordance with different fire durations.

A land manager treats all MUs in the landscapes except landscape HOM-M when fire duration is long (Figure 5.38 and Figure 5.39). Because of the longer fire duration in both weather conditions, fire spreads to a larger area (i.e. multiple MUs) under both mild and severe weather conditions. In particular, fire starting from untreated MUs of age class 3 spreads to adjacent MUs due to longer fire duration (for the base case, fire starting from untreated MUs of age class 3 does not spread to adjacent MUs). Therefore, the decision to remove all MUs with very high spread rates is not optimal. A land manager treats all MUs because both MUs with high spread rates and medium spread rates can be the "source" of fire spread.

However, when fire duration time is 50% longer than the base case, a land manager finds that harvesting MUs during the current period is optimal in some landscapes (CORD-H: Figure 5.38, PAT-M: Figure 5.39 and DONUT-H: Figure 5.39) because holding timber on site is too risky.



Actions			
cut = harvest	cut&fuel = harvest and fuel treatment	fuel = fuel treatment	grow = grow only

FIGURE 5.38: Optimal decisions for different longer fire durations (labeled "action")

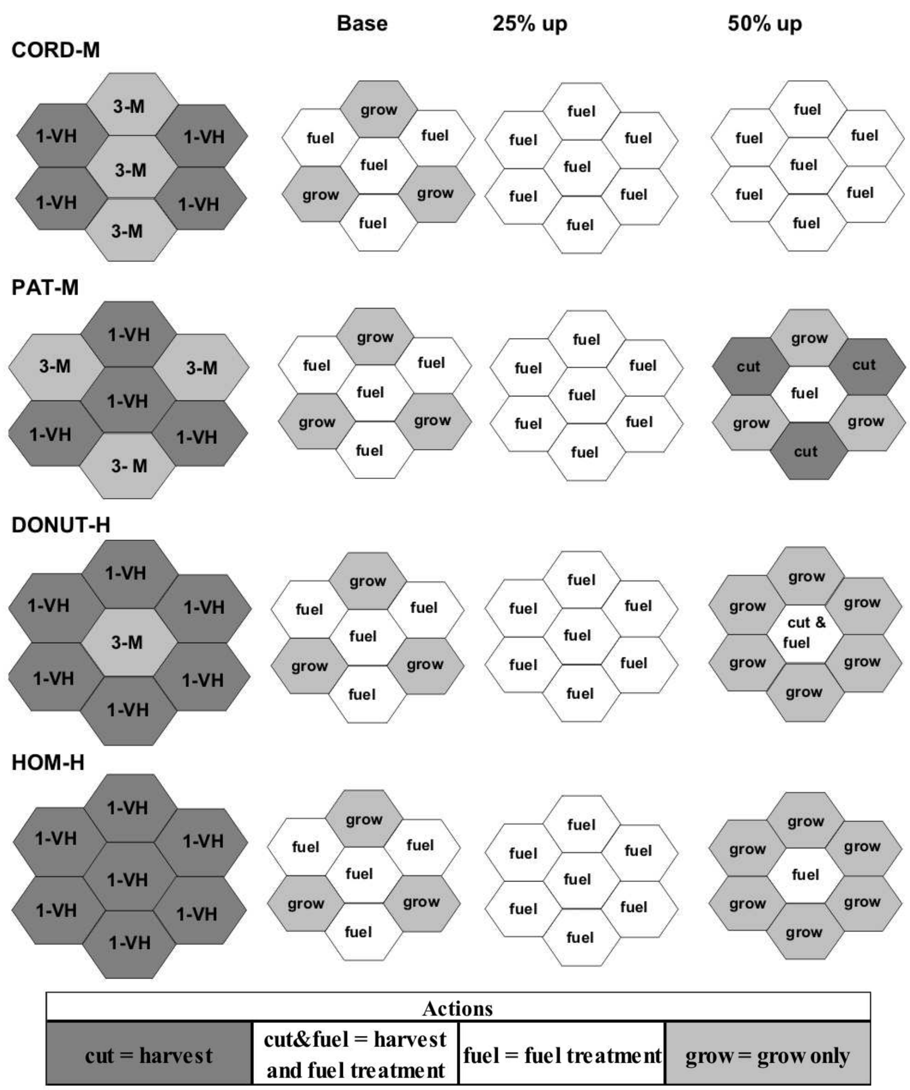
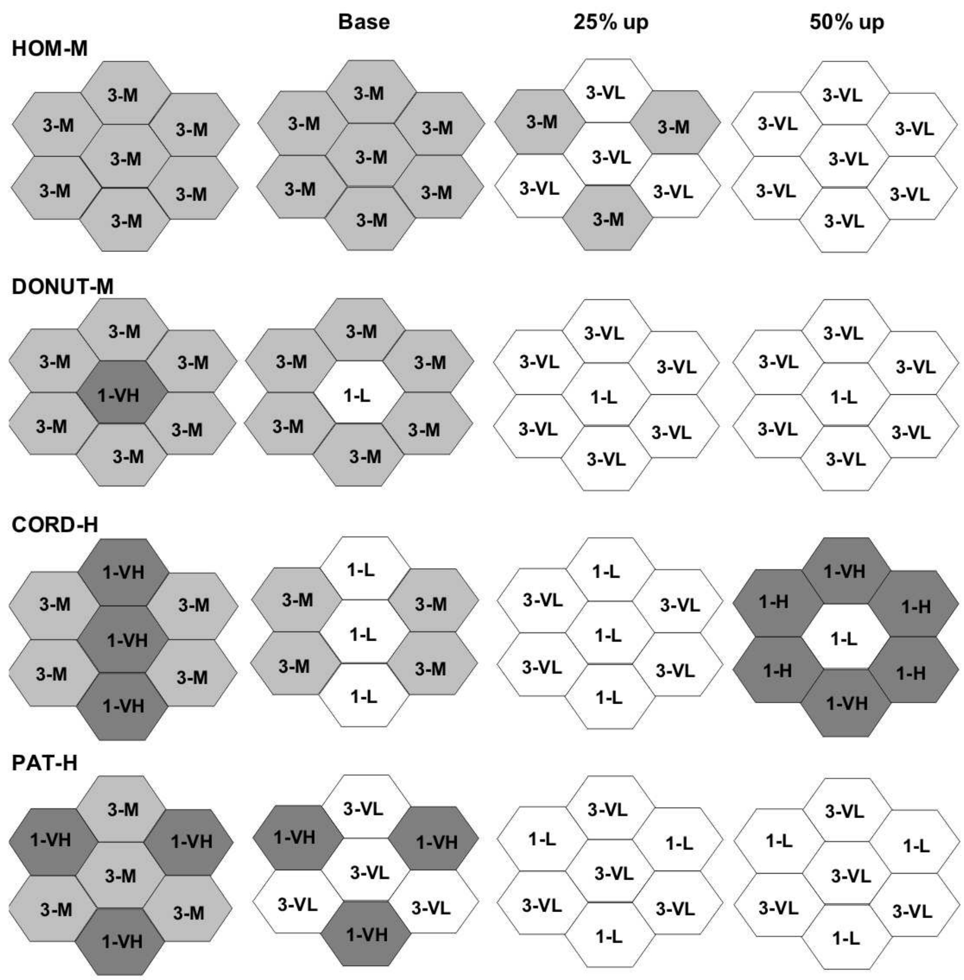
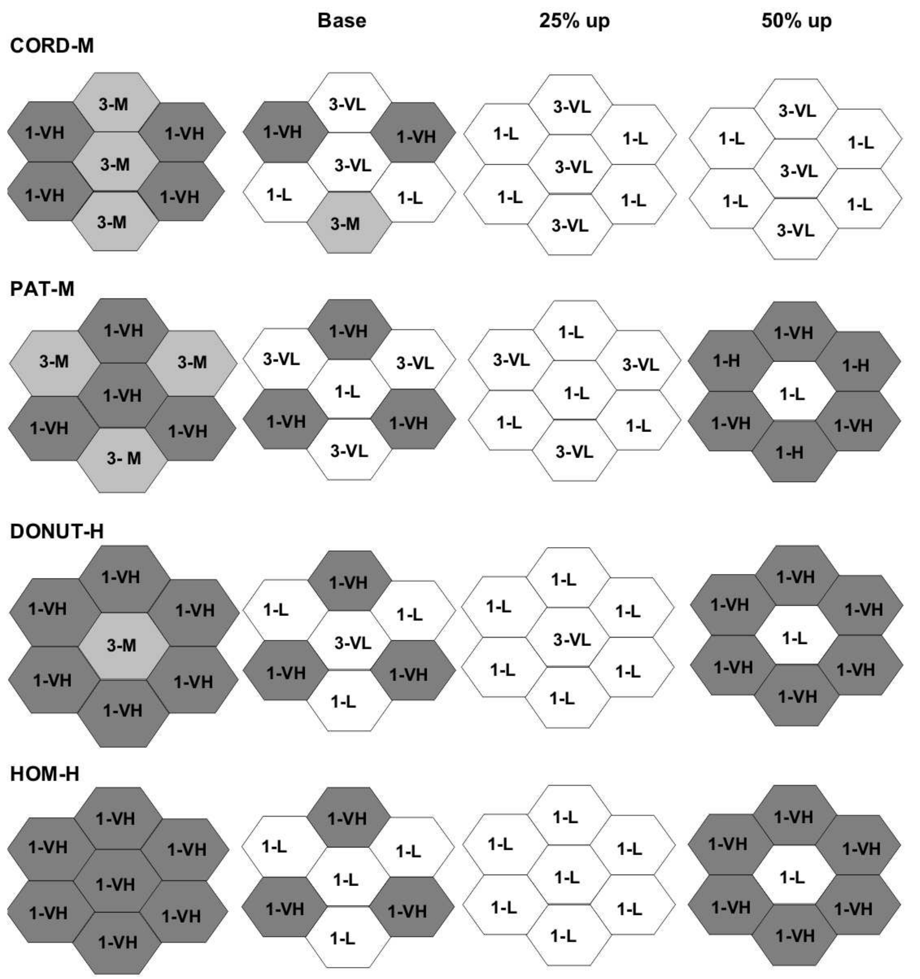


FIGURE 5.39: Optimal decisions for different longer fire durations (labeled "action")



Fuel Condition Class				
VL = Very Low	L = Low	M = Medium	H = High	VH = Very High

FIGURE 5.40: Optimal landscapes for different longer fire durations after optimal decision is applied (labeled "age class - fuel condition")



Fuel Condition Class				
VL = Very Low	L = Low	M = Medium	H = High	VH = Very High

FIGURE 5.41: Optimal landscapes for different longer fire durations after optimal decision is applied (labeled "age class - fuel condition")

5.3. Slope and Wind

In this section, I consider the effects of slope and wind on fire growth and behavior. First, the effect of wind on a flat landscape is examined. I assume that the land manager knows the prevailing wind direction. For each of eight different landscapes three wind directions are considered. Examining three wind directions has allowed me to gain insight into fuel management practices because it provides management solutions for a wide range of possible combinations of wind directions and spatial arrangement of fuel conditions[10]. Assuming a specific prevailing wind direction reduces the number of possible fire damage patterns because a specific prevailing wind direction leads to a specific fire growth pattern. However, ignition can start in any MU. The risk of fire damage in down-wind MUs tends to be higher than the base case, and the risk of fire damage in up-wind MUs tends to be lower than the base case.

These analyses are made for two purposes: 1) in order to understand how wind affects optimal decisions and, 2) to show that extreme weather conditions make fuel treatment ineffective and lead to more harvesting. These analyses will provide a basis for fire management in situations where wind is an important factor and a prevailing wind direction is known.

Second, the effects of slope are considered assuming that there is no wind. I assume that all MUs in a landscape have the same slope in terms of aspect and steepness. This analysis is conducted in order to see how management strategy will be changed depending on the slope and the location of an MU in relationship to the slope (i.e. the bottom, top

[10]Because all landscapes tested in this chapter are symmetric in terms of fuel (and stand age class) conditions, three wind directions provide enough combinations of wind directions and spatial arrangement of fuel conditions to draw general insights for fuel management.

or middle of the slope).

5.3.1. Winds

Two wind-speeds are considered. Henceforth, I call a wind speed of 40 km/hour "strong" and a wind speed of 5km/hour "weak". Three different wind directions are considered on a flat landscape. Suppose that MU0 is in the south-end of a landscape. The wind which blows from MU0 to MU3 is a "south wind". The wind which blows from MU1 to MU5 or from MU2 to MU4 is an "east wind". The wind which blows from MU1 to MU4 is a "south-east". Wind blows from one direction for the entire fire duration. Figure 5.42 and Figure 5.43 depict how the optimal decision changes in accordance with different south wind speeds. Figure 5.44 and Figure 5.45 depict the optimal landscape in the case of south mild winds after the optimal decision is applied. Figure 5.46 and Figure 5.47 depict how the optimal decision changes in accordance with different south-east wind speeds. Figure 5.48 and Figure 5.49 depict the optimal landscape in the case of south-east mild winds. Figure 5.50 and Figure 5.51 depict how the optimal decision changes in accordance with different east wind speeds. Figure 5.52 and Figure 5.53 depict the optimal landscape in the case of east mild winds after the optimal decision is applied.

When wind is strong, a land manager harvests all MUs with merchantable timber, except the one located upwind, and treats the center MU only if it has a very high spread rate (Figure 5.42, Figure 5.43, Figure 5.46, Figure 5.47, Figure 5.50 and Figure 5.51). A land manager leaves upwind MUs untreated (Figure 5.42, Figure 5.43, Figure 5.46, Figure 5.47, Figure 5.50 and Figure 5.51).

Upwind MUs are left untreated because a strong wind creates a very elongated fire following wind direction, which keeps the risk of fire damage in upwind MUs at a low level.

A land manager assigns fuel treatment in the center MU, only if it has a very high spread rate because by changing the fuel conditions in the center MU from a very high spread rate to a low spread rate, the risk of fire damage can be reduced in multiple downwind MUs.

The results suggest that when wind is strong, a spatial allocation of fuel management will have little impact on mitigating fire risk because fuel management becomes less effective under strong winds. This result is consistent with previous reports [64], which find that behaviors of wind-driven wildfires are rarely influenced by fuel treatments.

When wind is weak, a land manager follows a strategy which is specific to wind direction. For example, when the prevailing wind direction is south (Figure 5.42 and Figure 5.43), if the MUs located in the north end of a landscape (MU2, MU3 and MU4: downwind MUs) have merchantable timber, a land manager harvests these MUs during the current period (Figure 5.42 and Figure 5.43). On the other hand, if the MUs located in south end of a landscape (MU0, MU1 and MU5: upwind MUs) have merchantable timber, a land manager treats these MUs (Figure 5.42 and Figure 5.43).

A land manager harvests downwind MUs with merchantable timber during the current period because the risk of fire damage in these MUs is extremely high due to the fact that any fire ignition will reach these MUs. Even if all of the MUs in south end of a landscape MU0, MU1, MU5 (upwind MUs) and, the center MU6 are treated, the risk of value loss in the MUs located in the north end (downwind) are high. A land manager treats upwind MUs with merchantable timber because by treating these MUs, the risk of fire damage can be reduced to a level where a land manager prefers to take the risk in exchange for the opportunity of harvesting at a financially optimal rotation age.

A land manager leaves MUs with very high spread rates untreated unless they are located in the center (Figure 5.42 and Figure 5.43). A land manager generally treats the center MU regardless of its age or the initial spatial configuration (Figure 5.42 and Figure 5.43). However, there are exceptions to this "rule". In landscapes DONUT-H and HOM-H, MUs with very high spread rates, which are in the north of these landscapes (downwind), will be treated (Figure 5.43).

This is because 1) MUs with very high spread rates are the second most valuable MUs in the landscape 2) because MUs of age class 1 cannot be harvested, the best thing that a land manager can do is to protect the second most valuable MUs, 3) the MUs in the north end of a landscape (downwind) face a higher risk than those in the south end (upwind). Therefore, the risk reduction from fuel treatment is large and the expected NPV increases significantly.

When the prevailing wind direction is south-east, a land manager implements the same management strategies used in south wind cases (Figure 5.46 and Figure 5.47). A land manager harvests downwind valuable MUs, while he or she treats upwind valuable MUs (Figure 5.46 and Figure 5.47). A land manager leaves MUs with very high spread rates untreated unless they are located in the center (Figure 5.46 and Figure 5.47) in landscapes except landscapes DONUT-H and HOM-H. In these landscapes, the downwind MUs with high spread rates is treated because of a higher risk of fire damage (Figure 5.47).

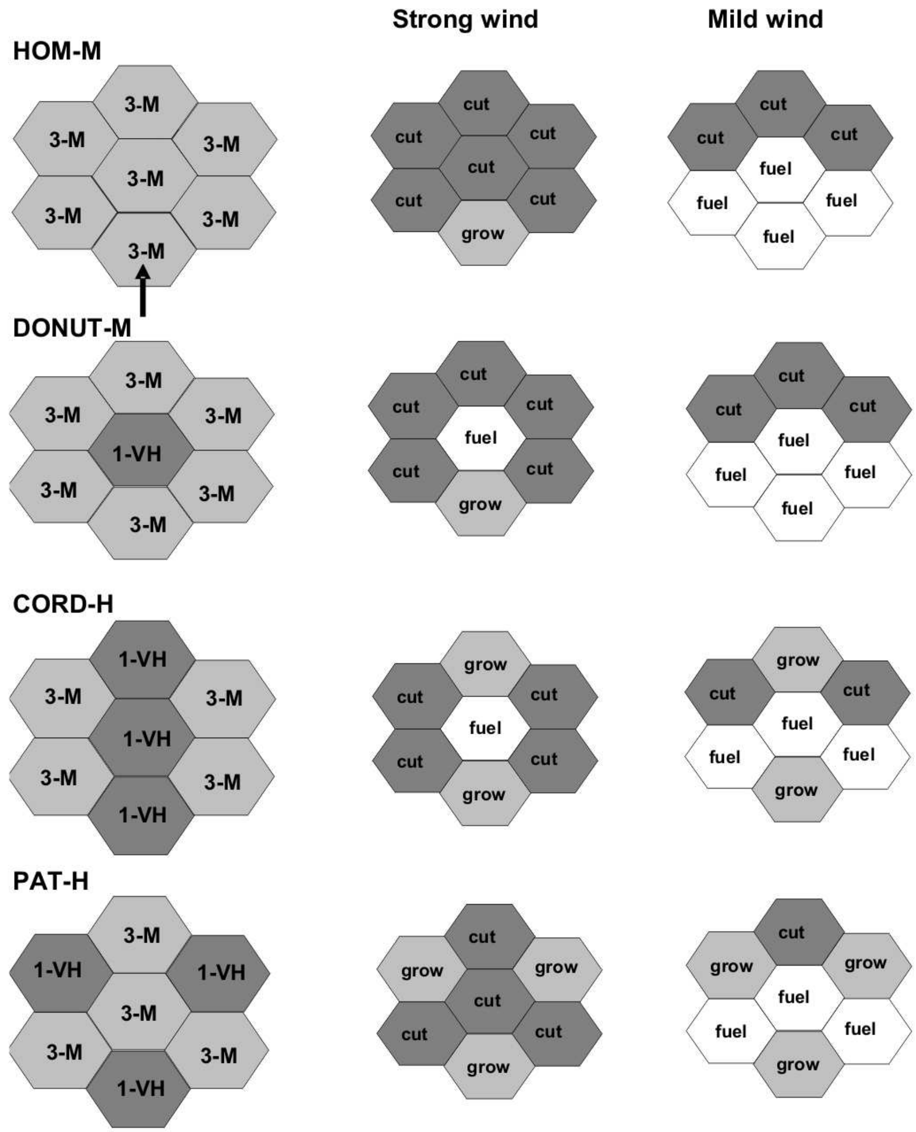
When the prevailing wind direction is east, a land manager applies slightly different management strategies from previous two wind cases. A land manager harvests valuable MUs in the middle lane during the current period in all landscapes except landscape PAT-H where only one upwind MU has a very high spread rate (Figure 5.50).

A land manager harvests valuable MUs in the middle lane because of the location of MUs relative to each other and relative to wind direction. There are two upwind MUs, two downwind MUs, and three MUs in the middle lane. The two upwind MUs (MU1 and MU2) have a lower risk of fire damage. The MUs in the middle lane (MU0, MU3 and

MU6) have a higher risk because they are burned more frequently; they are burned not only from "self-ignition" but also from fire ignition in MU1 and MU2 regardless of fuel conditions.

Unlike previous two wind cases, a land manager sometimes treats downwind MUs with very high spread rates, when the prevailing wind direction is east (Figure 5.50 and Figure 5.51). In landscape CORD-M, a land manager treats downwind MUs with very high spread rates (Figure 5.51).

Because of "new harvesting rule" applied in the middle lane MUs, the center MU has the fuel condition of a high spread rate after it is harvested and becomes the "path" to link upwind MUs to downwind MUs. Therefore, in landscape CORD-M, the risk of value loss in multiple MUs increases if a land manager leaves any of the MUs with very high spread rates (age class 1) untreated. Treating downwind MUs with very high spread rates will mitigate the risk of value loss.



Actions			
cut = harvest	cut&fuel = harvest and fuel treatment	fuel = fuel treatment	grow = grow only

FIGURE 5.42: Optimal decisions for different south wind speeds (labeled "action")

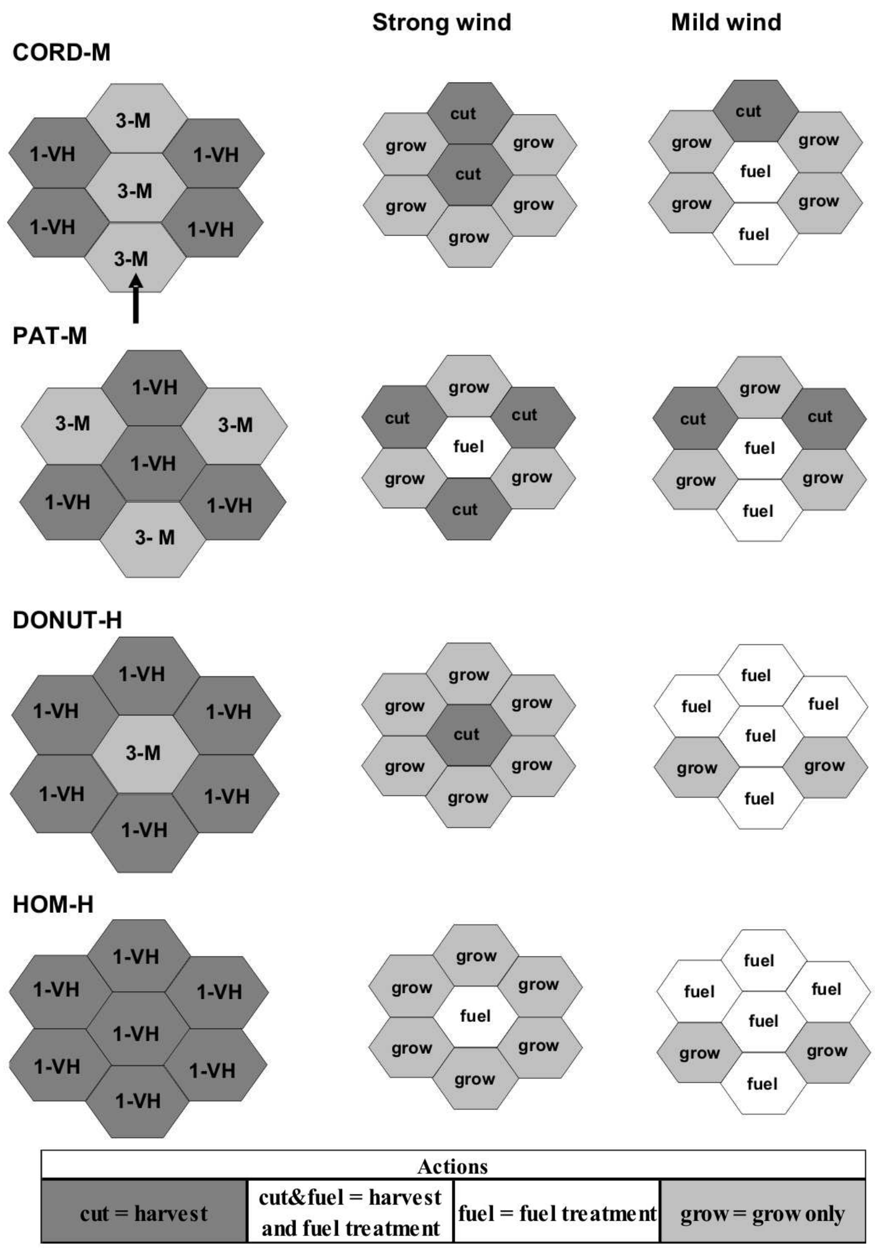
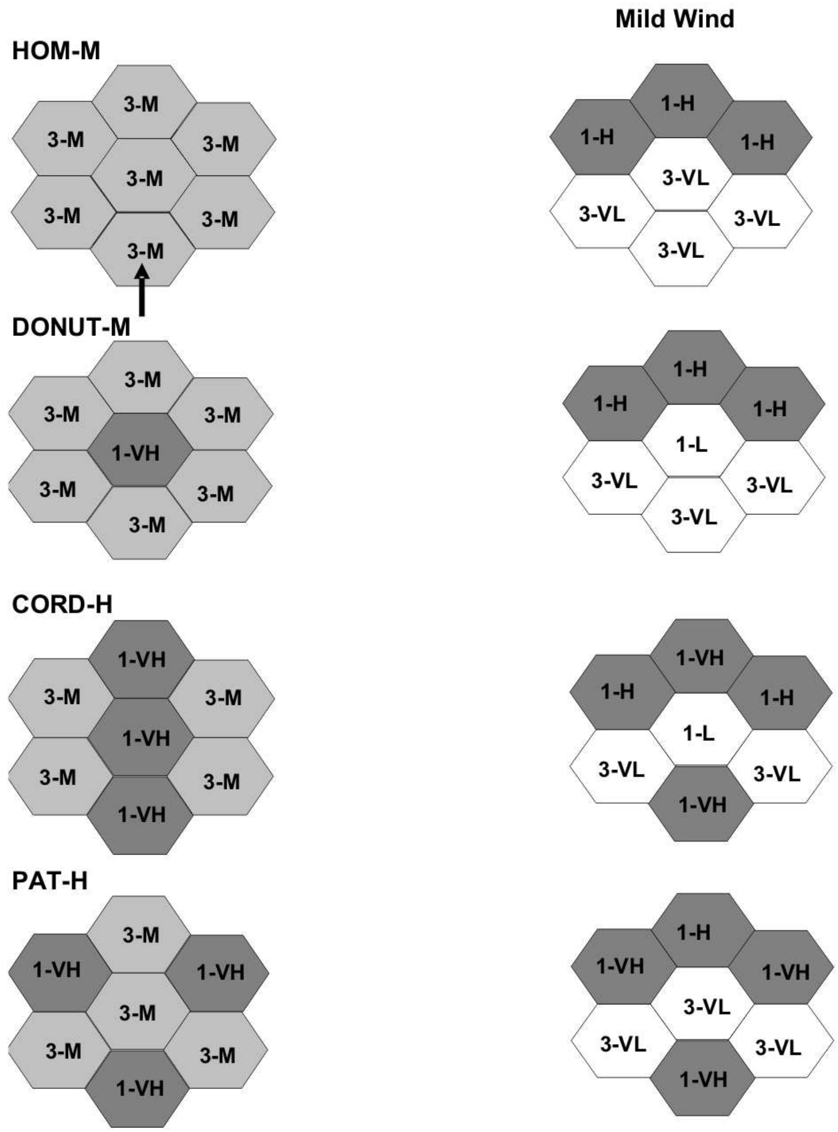
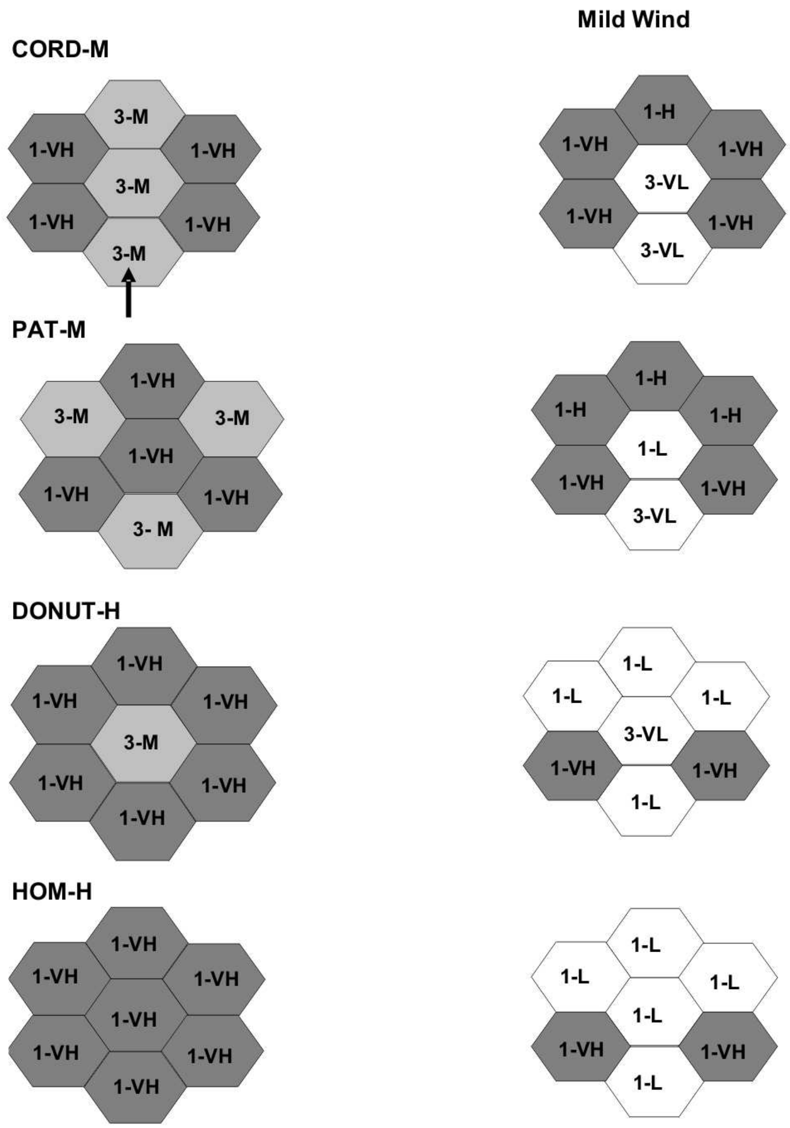


FIGURE 5.43: Optimal decisions for different south wind speeds (labeled "action")



Fuel Condition Class				
VL = Very Low	L = Low	M = Medium	H = High	VH = Very High

FIGURE 5.44: Optimal landscapes for different south wind speeds after optimal decision is applied (labeled "age class - fuel condition")



Fuel Condition Class				
VL = Very Low	L = Low	M = Medium	H = High	VH = Very High

FIGURE 5.45: Optimal landscapes for different south wind speeds after optimal decision is applied (labeled "age class - fuel condition")

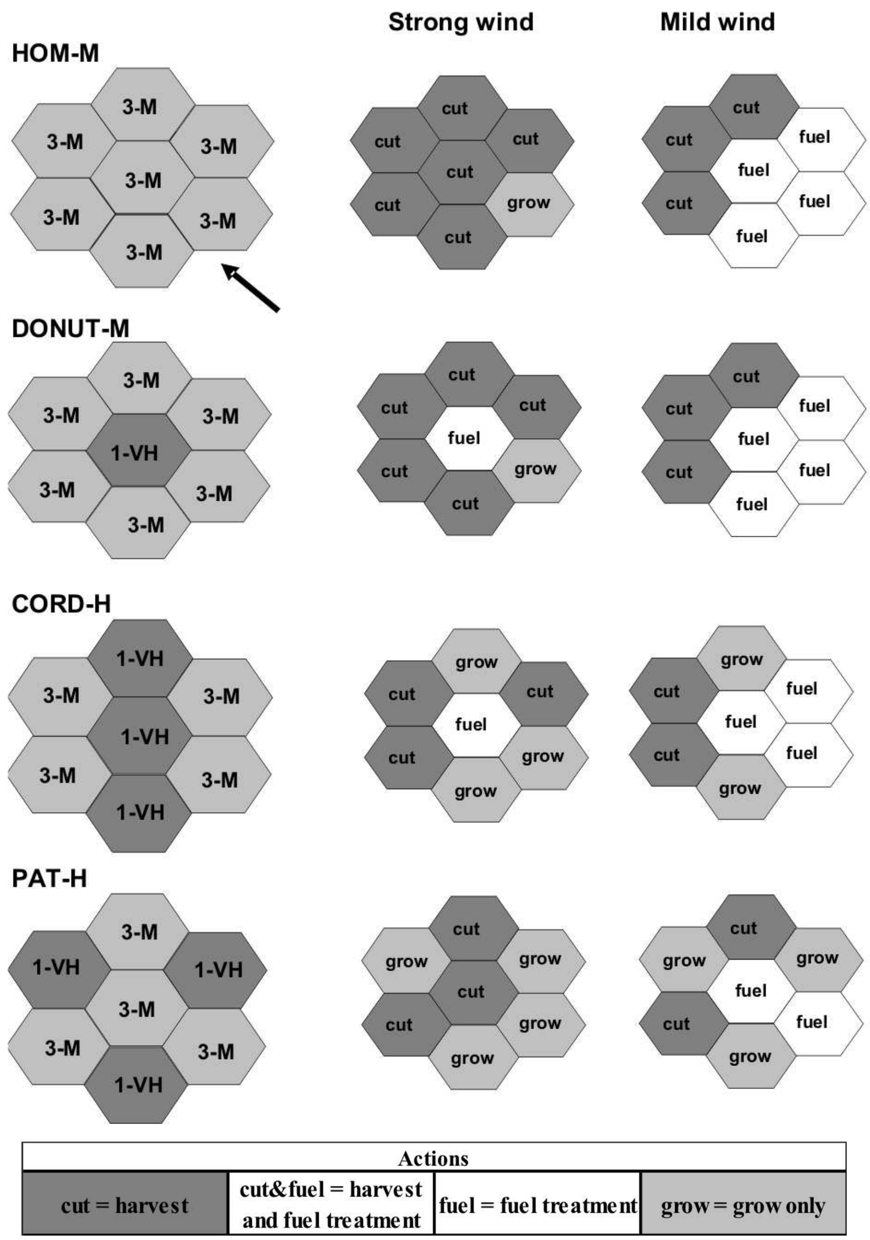
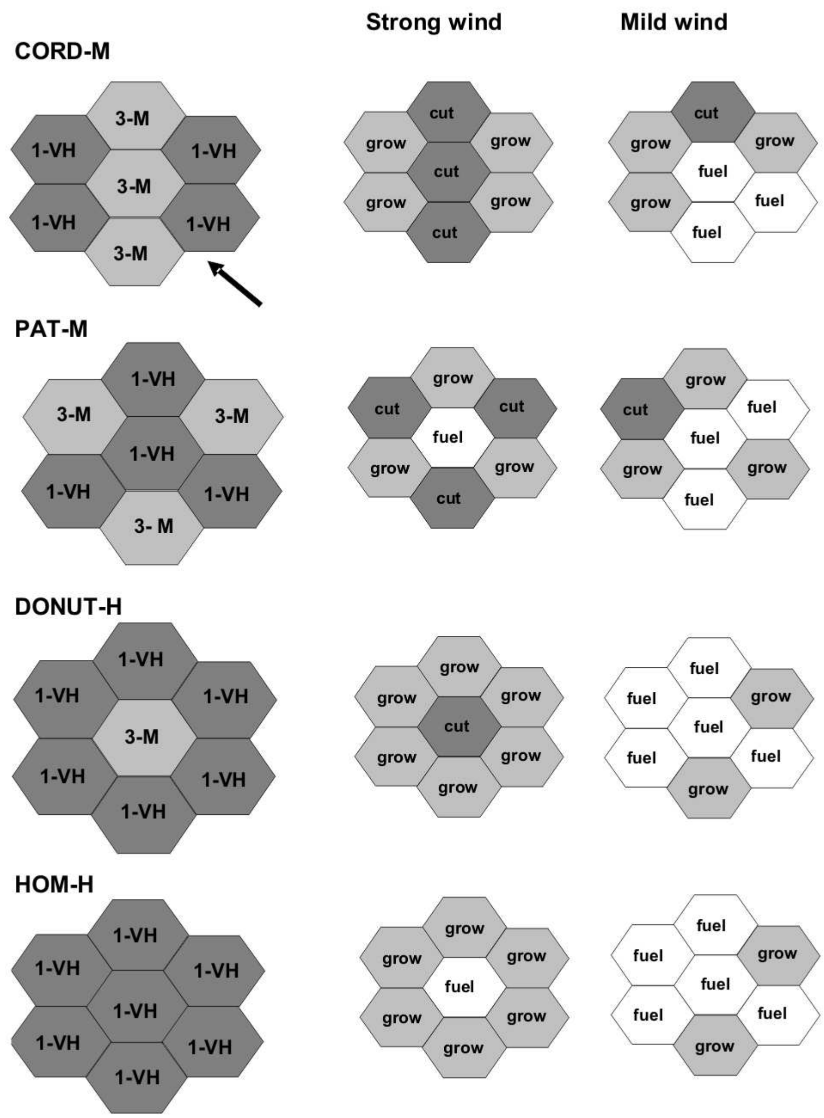
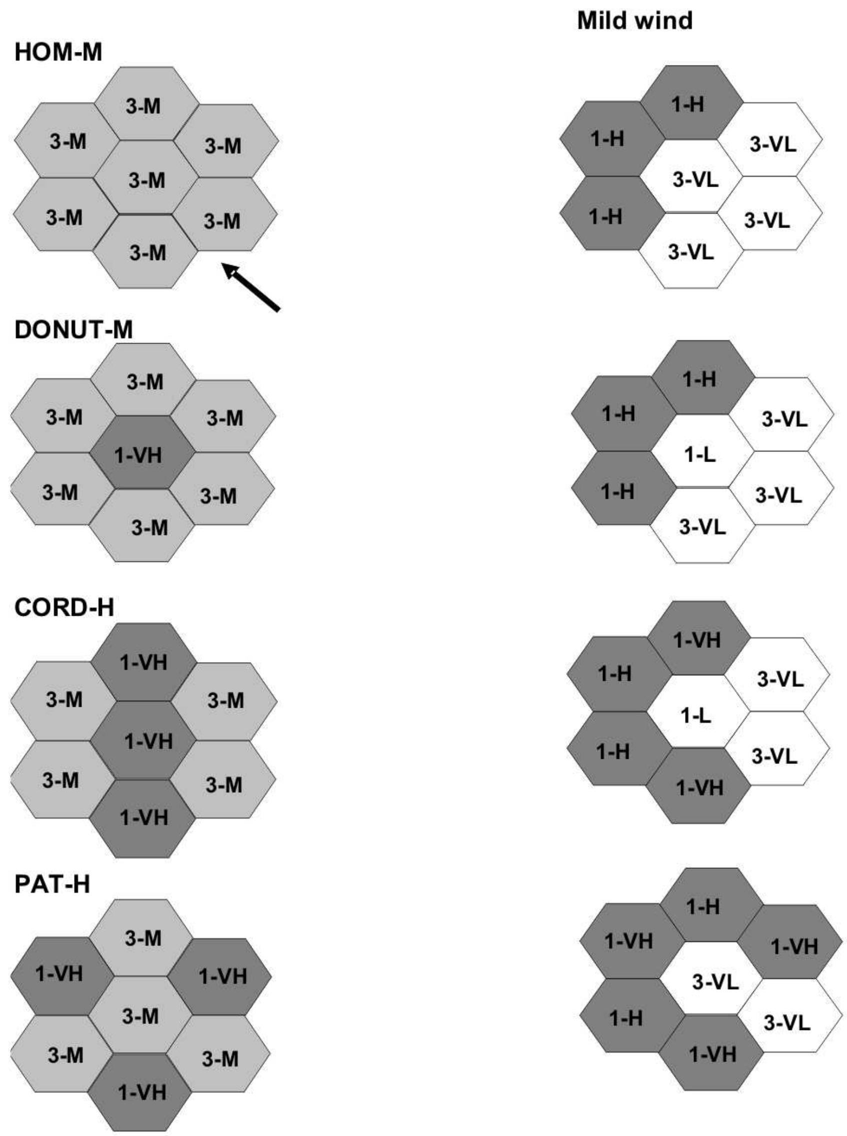


FIGURE 5.46: Optimal decisions for different southeast wind speeds (labeled "action")



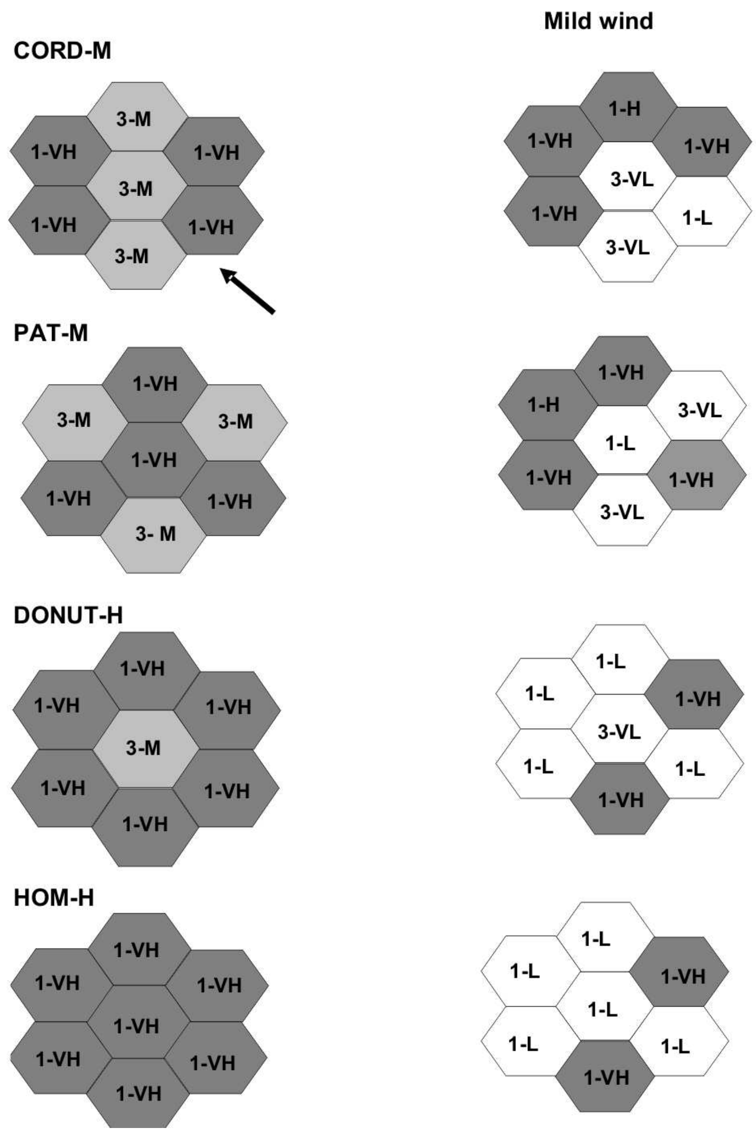
Actions			
cut = harvest	cut&fuel = harvest and fuel treatment	fuel = fuel treatment	grow = grow only

FIGURE 5.47: Optimal decisions for different southeast wind speeds (labeled "action")



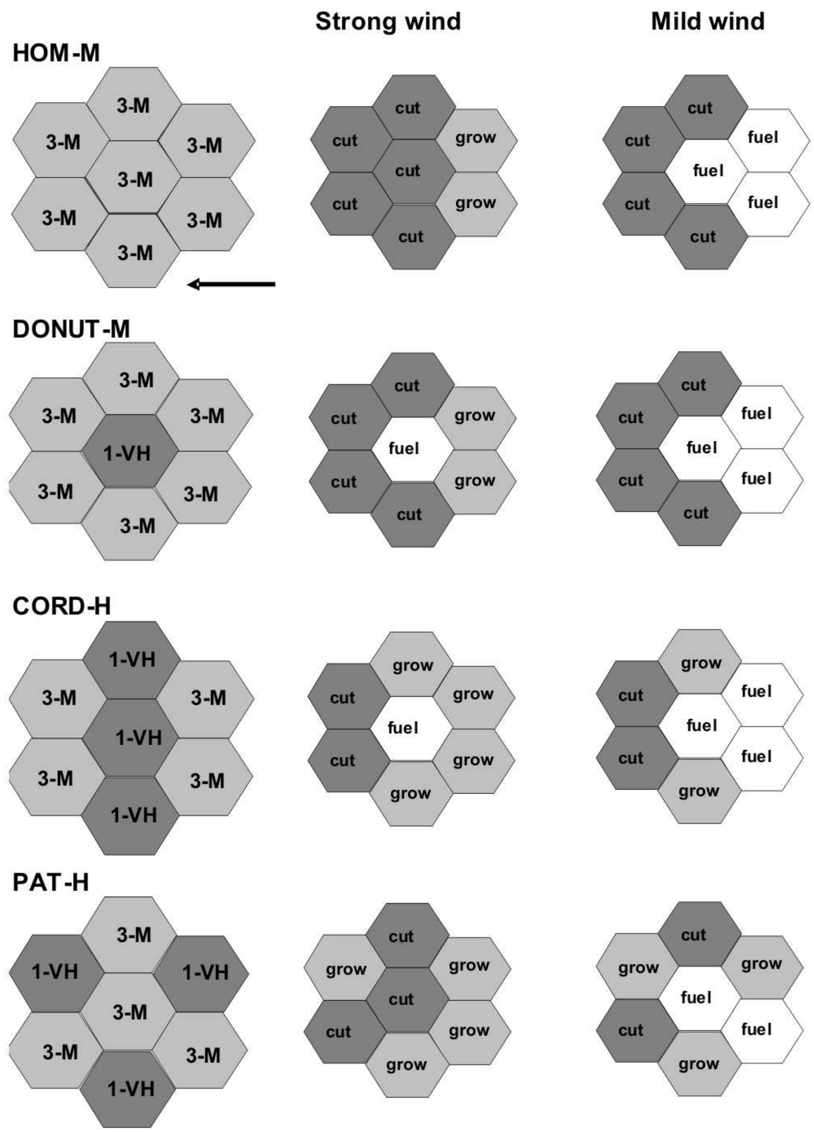
Fuel Condition Class				
VL = Very Low	L = Low	M = Medium	H = High	VH = Very High

FIGURE 5.48: Optimal landscapes for different southeast wind speeds after optimal decision is applied (labeled "age class - fuel condition")



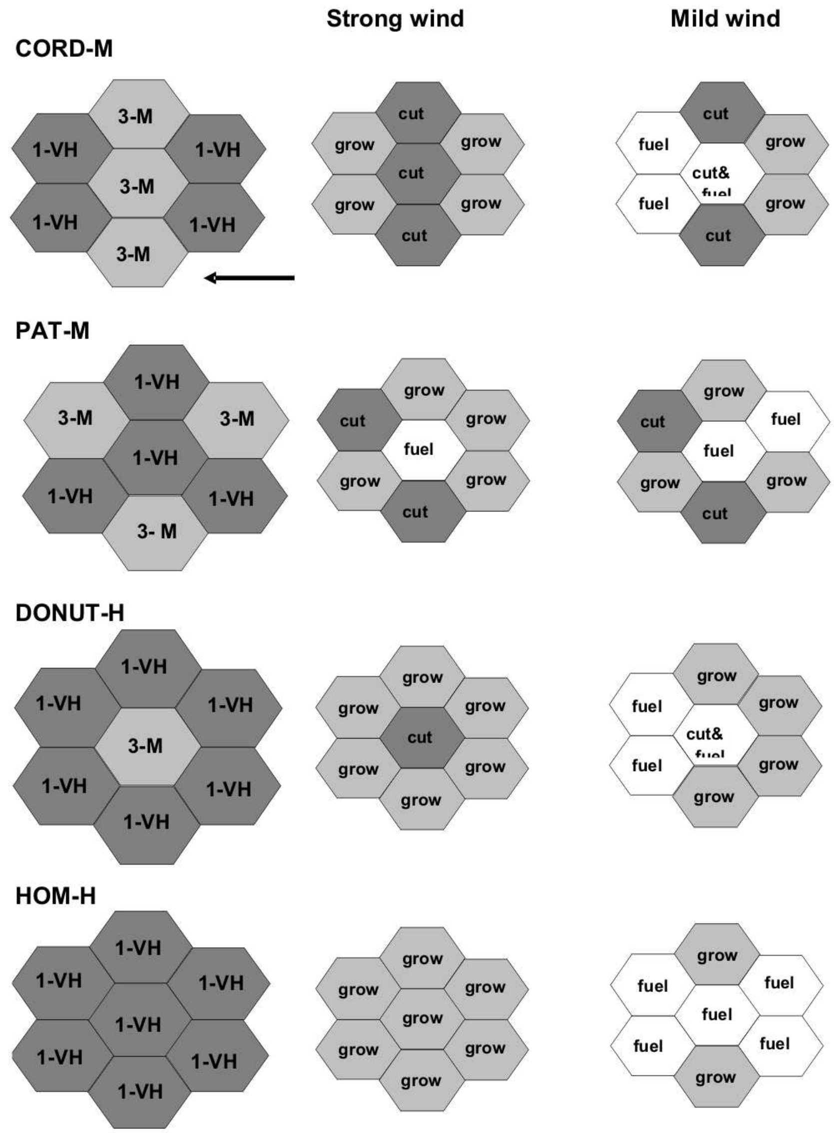
Fuel Condition Class				
VL = Very Low	L = Low	M = Medium	H = High	VH = Very High

FIGURE 5.49: Optimal landscapes for different southeast wind speeds after optimal decision is applied (labeled "age class - fuel condition")



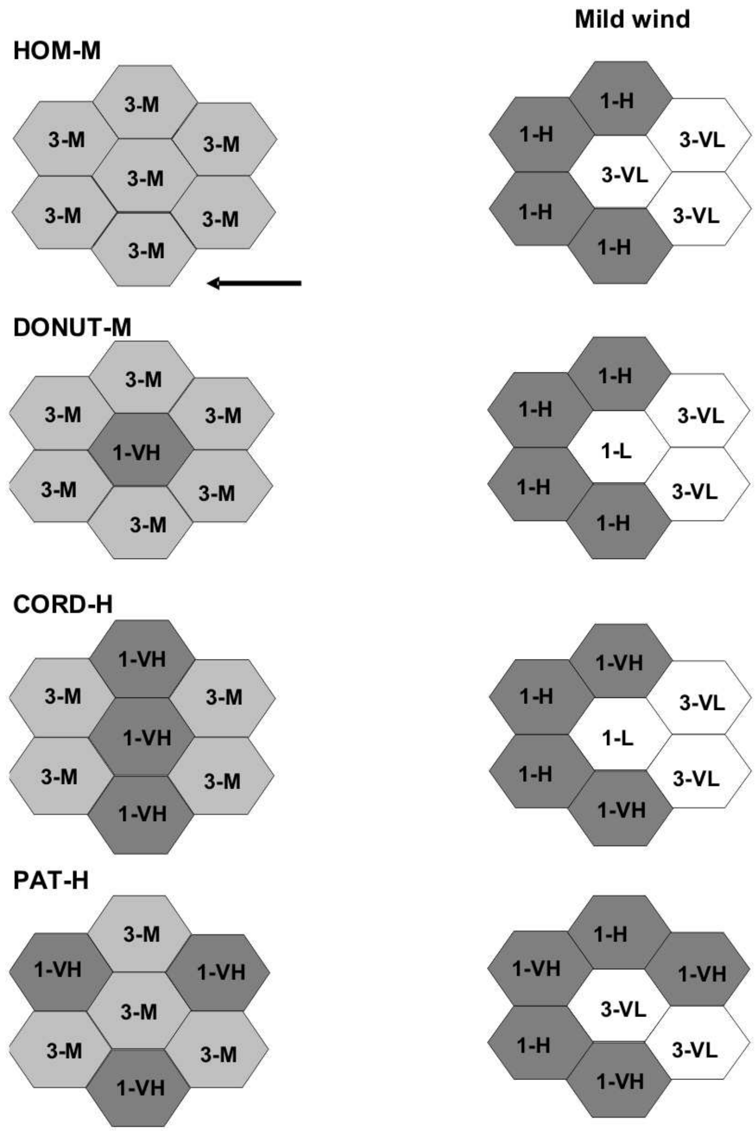
Actions			
cut = harvest	cut&fuel = harvest and fuel treatment	fuel = fuel treatment	grow = grow only

FIGURE 5.50: Optimal decisions for different east wind speeds (labeled ”action”)



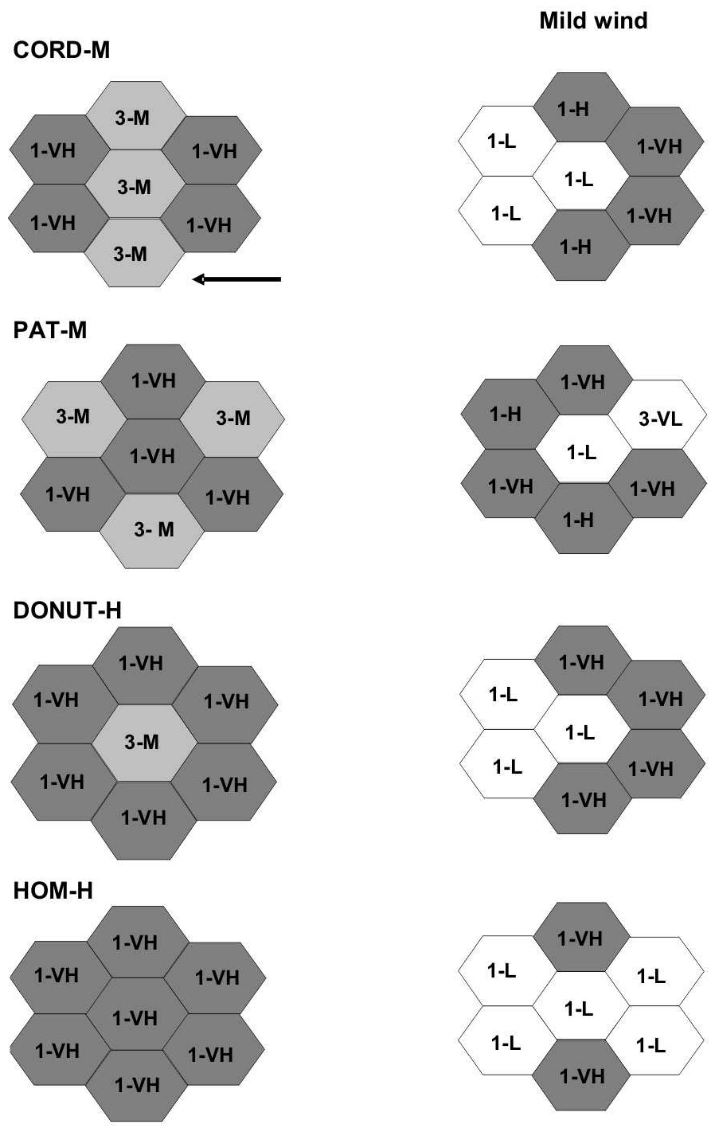
Actions			
cut = harvest	cut&fuel = harvest and fuel treatment	fuel = fuel treatment	grow = grow only

FIGURE 5.51: Optimal decisions for different east wind speeds (labeled "action")



Fuel Condition Class				
VL = Very Low	L = Low	M = Medium	H = High	VH = Very High

FIGURE 5.52: Optimal landscapes for different east wind speeds after optimal decision is applied (labeled "age class - fuel condition")



Fuel Condition Class				
VL = Very Low	L = Low	M = Medium	H = High	VH = Very High

FIGURE 5.53: Optimal landscapes for different east wind speeds after optimal decision is applied (labeled ”age class - fuel condition”)

5.3.2. Slopes

In this section, I examine the effects of both steep and low slopes on fuel management decisions. The model uses 10% and 40% for low slope and steep slope respectively. Fire spreads more quickly in an upward direction (from the base to the top) than it does going down or on a flat surface. I assume that the ignition probability is independent of slope in order to focus on spatial risk generated from the mechanism of fire spread on slope[11]. Three different slope aspects are considered. Examining three different slope aspects has allowed me to gain insight into fuel management practices because it provides management solutions for a wide range of possible combinations of slope aspects and spatial arrangement of fuel conditions[12]. The upward slope from MU0 to MU3 is the south-facing slope. The upward slope from MU1 to MU5 or MU2 to MU4 is the east-facing slope. The upward slope from MU1 to MU4 is the south-east-facing slope. Figure 5.54 and Figure 5.55 depict how the optimal decision changes in accordance with different south slope steepness. Figure 5.56 and Figure 5.57 depict the optimal landscape in the case of south low slope after the optimal decision is applied. Figure 5.58 and Figure 5.59 depict how the optimal decision changes in accordance with different south-east slope steepness. Figure 5.60 and Figure 5.61 depict the optimal landscape in the case of south-east low slope after the optimal decision is applied. Figure 5.62 and Figure 5.63 depict how the optimal decision changes in accordance with different east slope steepness. Figure 5.64 and Figure 5.65 depict the optimal landscape in the case of east low slope after the optimal decision is applied.

[11] Wildfire scientists have found that ignition probability depends on topographic conditions [65] [53] [66]

[12] Because all landscapes tested in this chapter are symmetric in terms of fuel (and stand age class) conditions, three slope aspects provide enough combinations of slope aspects and spatial arrangement of fuel conditions to draw general insights for fuel management.

A land manager harvests all MUs with merchantable timber and does not assign fuel treatment in landscapes which contains a steep slope (Figure 5.54, Figure 5.55, Figure 5.58, Figure 5.59, Figure 5.62 and Figure 5.63). The results are slightly different than they are in the case of strong wind 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 difference arises because, unlike the case of strong wind that creates an elongated shape of fire following the wind direction, a steep slope does not create such an elongated fire and, therefore, fire which ignites from MUs on the middle of the slope can also burn the MUs at the bottom of the slope. (On the other hand, upwind MUs are not burned from an ignition from downwind MUs.) Therefore, the risk of fire damage in these MUs at the bottom of the slope is higher compared to that in downwind MUs. Then, the optimal decision involves harvesting of these MUs because it is too risky to hold timber in the MUs at the bottom of the slope. The results indicate that when the slope is steep, the spatial allocation of fuel management may have little impact on mitigating the risk of fire damage because fuel management becomes less effective on a steep slope.

A land manager follows a strategy that is specific to each slope aspect in the case of a low slope. A land manager finds strategies that are similar to those of the case of mild wind. For example, when a landscape has a south-facing slope, a land manager treats MUs at the bottom of the slope (MU0, MU1, and MU5), if these MUs have merchantable timber (Figure 5.54 and Figure 5.55). A land manager harvests MUs at the top of the slope (MU2, MU3, and MU4) during the current period, if these MUs have merchantable timber (Figure 5.54 and Figure 5.55). Unlike the case of a south wind, a land manager harvests the center MU with merchantable timber (Figure 5.54 and Figure 5.55).

A land manager harvests the center MU with merchantable timber because the shape of the fire is not as elongated as it is when there is a wind. Therefore, slope aspect has less of an effect on fuel management decisions than wind does and ignitions from MUs at the top of the slope also spreads to the center MU, which increases the risk of value loss in this center MU.

A land manager does not treat MUs with a very high spread rate that are located at the top of the slope, while he or she treats MUs with very high spread rates that are located at the bottom of the slope when a landscape has a south-facing slope (Figure 5.54 and Figure 5.55).

A land manager treats MUs with very high spread rates that are located at the bottom of the slope because, if MUs with a high spread rate at the bottom of the slope are left untreated, the risk of value loss in multiple MUs increases due to the rapid spread upslope. (On the other hand, the risk of value loss in other MUs is relatively small, when MUs with very high spread rates at the top of the slope are left untreated. Fire spreads to the center MU that is harvested and has age class 1)

However, there are exceptions to this strategy. For example, in landscape PAT-H, a land manager harvests MU1 and MU5 rather than apply fuel treatment during the current period (Figure 5.54) and treats MU2 and MU4, which have very high spread rates and are located at the top of the slope (Figure 5.54).

The difference arises because the decision to harvest MU1, MU5, and MU6 results in a landscape consisting of only MUs with high spread rates, if MU2 and MU4 are not treated. The risk of value loss in multiple MUs increases in this landscape because a single ignition burns multiple MUs. Therefore, a land manager treats MU2 and MU4 so that reduction of the expected NPV from fire damage can be small. In this landscape, the decision to prevent the spread of fire is of a high priority, after a land manager harvests valuable MUs of age class 3 during the current period.

In landscapes that have a south-east-facing slope, a land manager follows the management strategies for a south-facing slope except in landscape CORD-M (Figure 5.58 and Figure 5.59). In landscape CORD-M, a land manager treats MUs with very high spread rates that are located at the top of the slope (Figure 5.59). In this landscape, a land manager treats all MUs with very high spread rates (Figure 5.59). A land manager finds that it is optimal to treat the center MU and wait for the financial optimal rotation age if all MUs with very high spreads rates are treated.

When a landscape has an east-facing slope, a land manager implements slightly different management strategies from the previous two slope cases (Figure 5.62 and Figure 5.63). For example, in landscape CORD-H, a land manager does not harvest valuable MUs located at the top of the slope (Figure 5.62).

The difference arises mainly because of the location of MUs relative to each other and relative to the position of the slope (i.e. the top of the slope or the bottom of the slope). In an east-facing landscape, two MUs, MU1 and MU2, are located at the bottom of the slope. Two MUs, MU4 and MU5, are located at the top of the slope. Three MUs, MU0, MU3 and MU6, are located in the middle of the slope. Then, by treating all MUs in the middle and at the bottom of the slope a land manager can reduce the risk of value loss by fire damage to the level at which a land manager prefers to take in exchange for the opportunity of harvesting at the financial optimal rotation age.

Unlike previous two slope cases, a land manager leaves MUs with very high spread rates, which are located at the bottom of the slope, untreated in landscapes CORD-M, DONUT-H, and HOM-H (Figure 5.63). Leaving MUs with very high spread rates at the bottom of the slope untreated is optimal because both MUs at the bottom of the slope have very high spread rates, treating one of these MUs is less effective in terms of reducing the risk of fire damage in adjacent MUs as well as in these MU themselves.

In landscape CORD-M, DONUT-H, and HOM-H, a land manager treats MUs with very high spread rates that are located at the top of the slope in these landscapes (Figure 5.63) because MUs with very high spread rates, which have an age class of one, become valuable after the MUs of age class 3 have been harvested, a land manager has an incentive to protect these MUs of age class 1 (harvesting MUs of age class 1 is not allowed and the best thing that a land manager can do is to protect these MUs) and also because the risk of fire damage is higher in MUs at the bottom of the slope, the benefits of protection will also be high in these MUs.

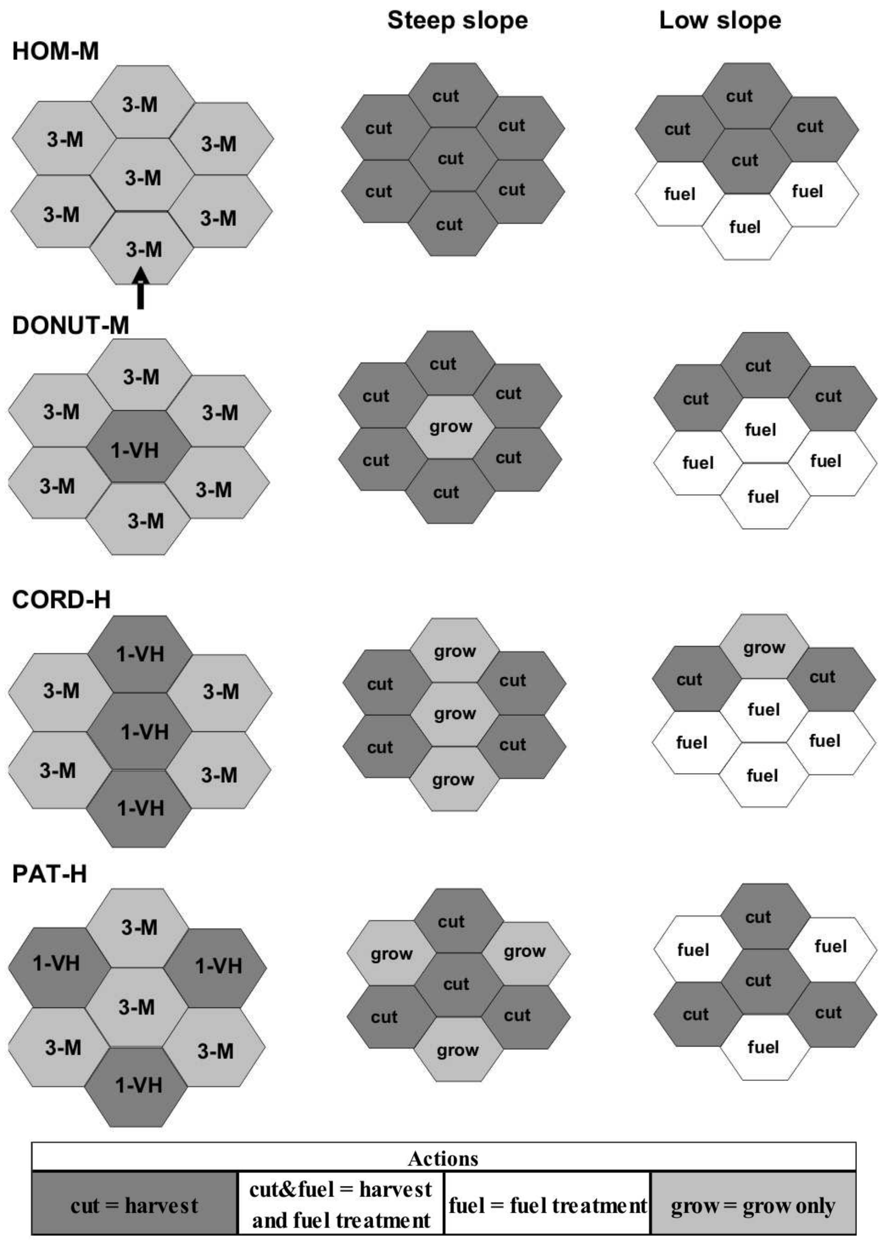
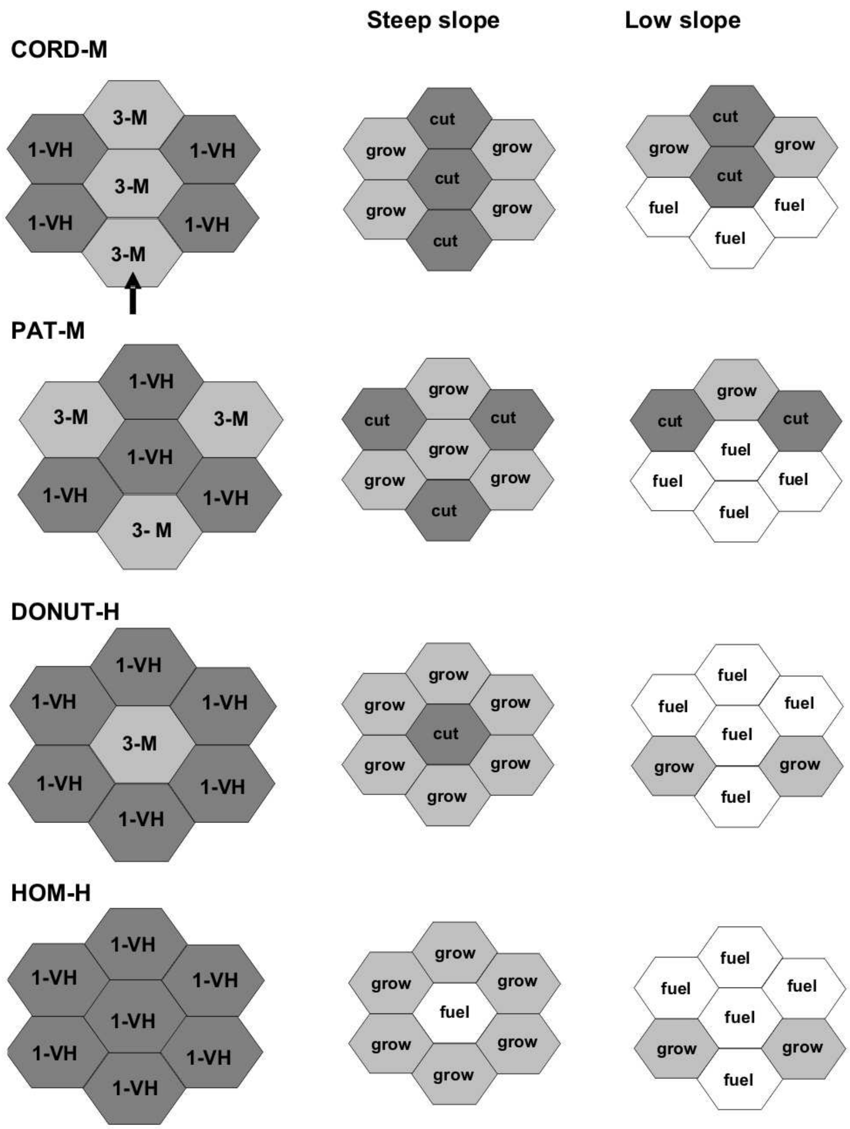
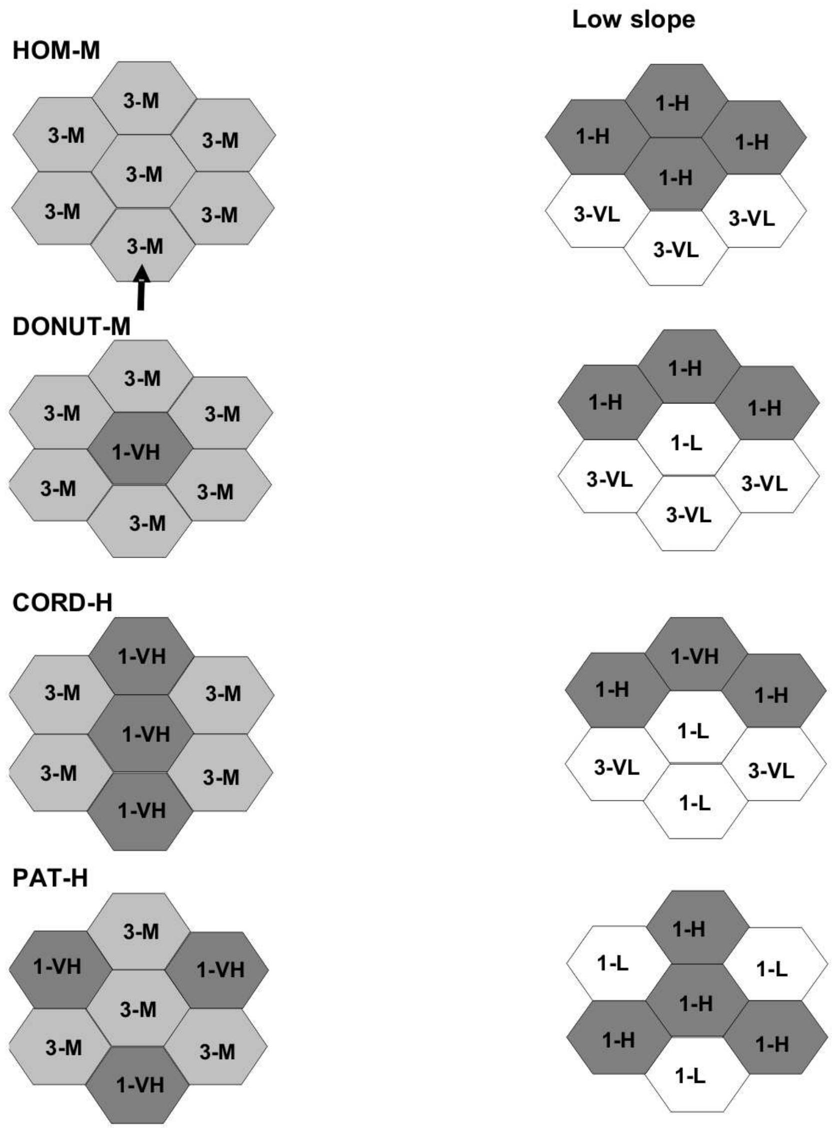


FIGURE 5.54: Optimal decisions for different south slope steepness (labeled ”action”)



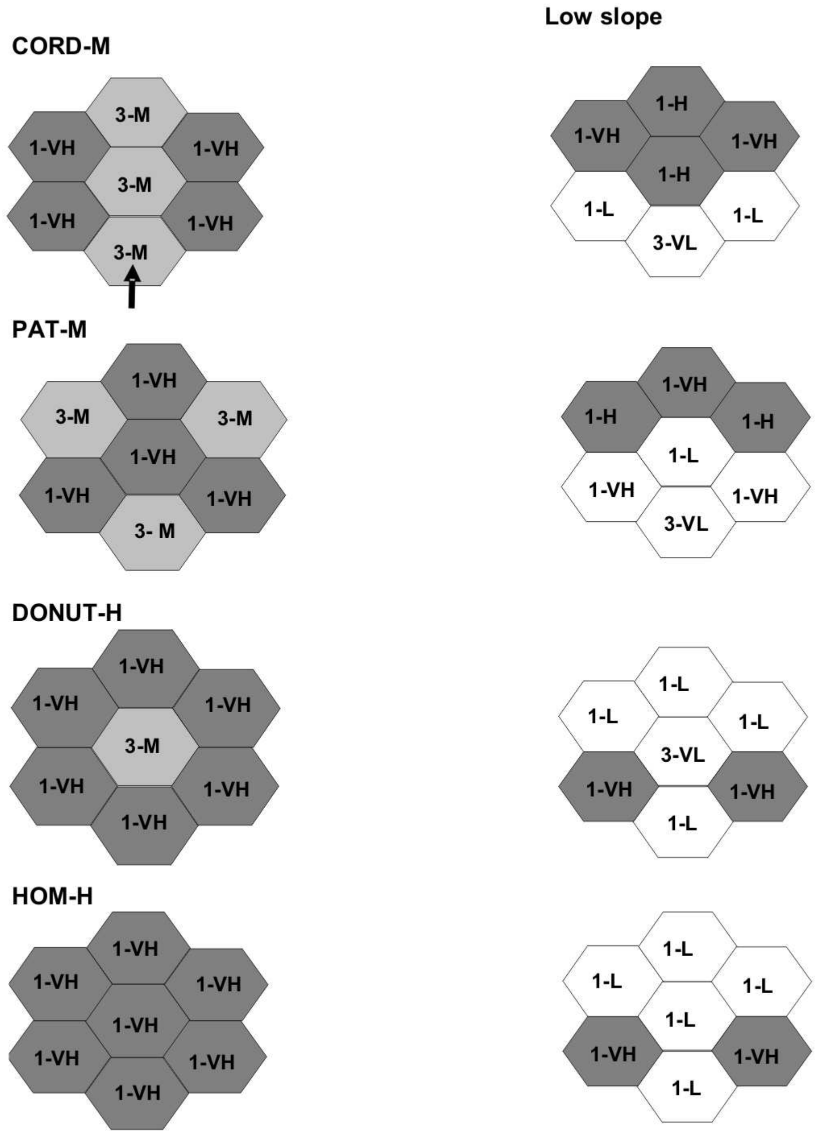
Actions			
cut = harvest	cut&fuel = harvest and fuel treatment	fuel = fuel treatment	grow = grow only

FIGURE 5.55: Optimal decisions for different south slope steepness (labeled "action")



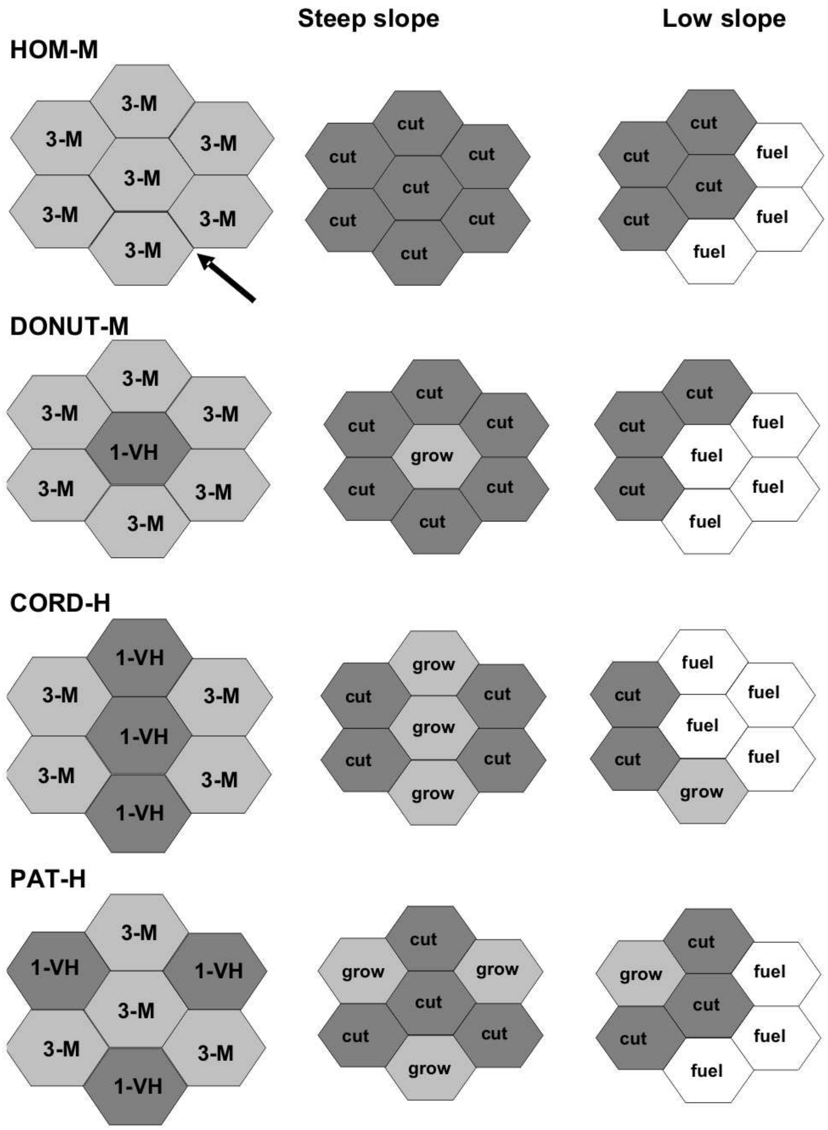
Fuel Condition Class				
VL = Very Low	L = Low	M = Medium	H = High	VH = Very High

FIGURE 5.56: Optimal landscapes for different south slope steepness after optimal decision is applied (labeled "age class - fuel condition")



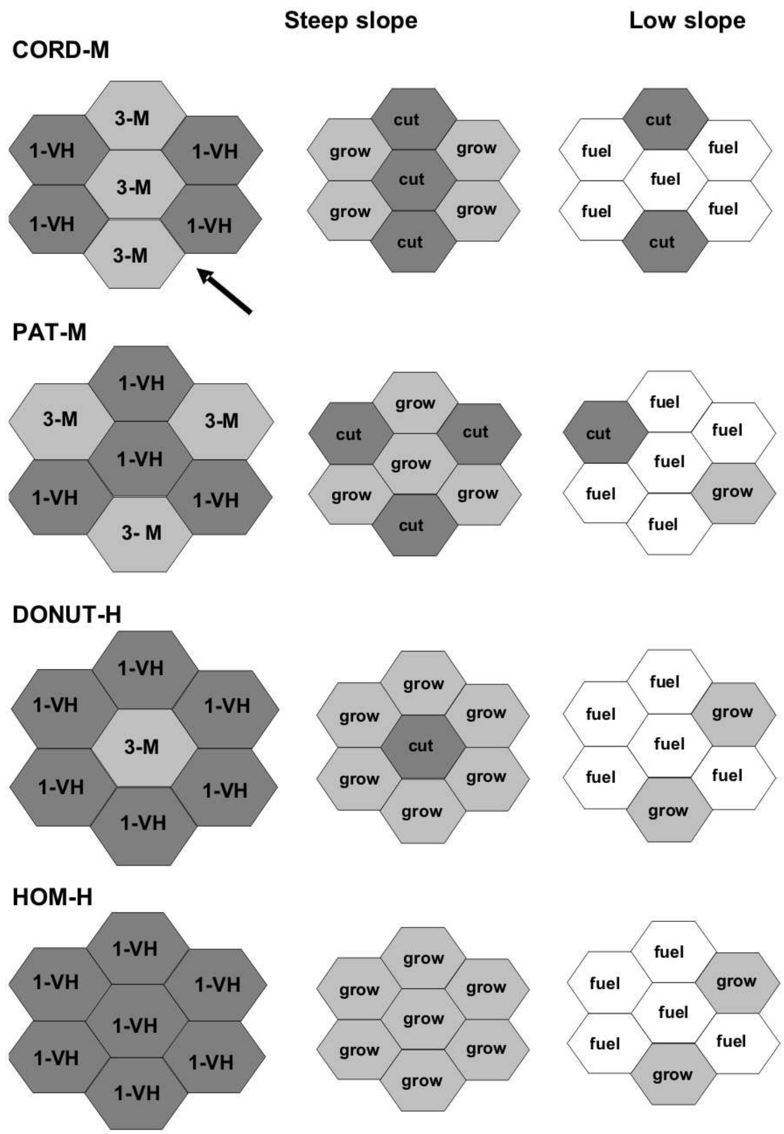
Fuel Condition Class				
VL = Very Low	L = Low	M = Medium	H = High	VH = Very High

FIGURE 5.57: Optimal landscapes for different south slope steepness after optimal decision is applied (labeled "age class - fuel condition")



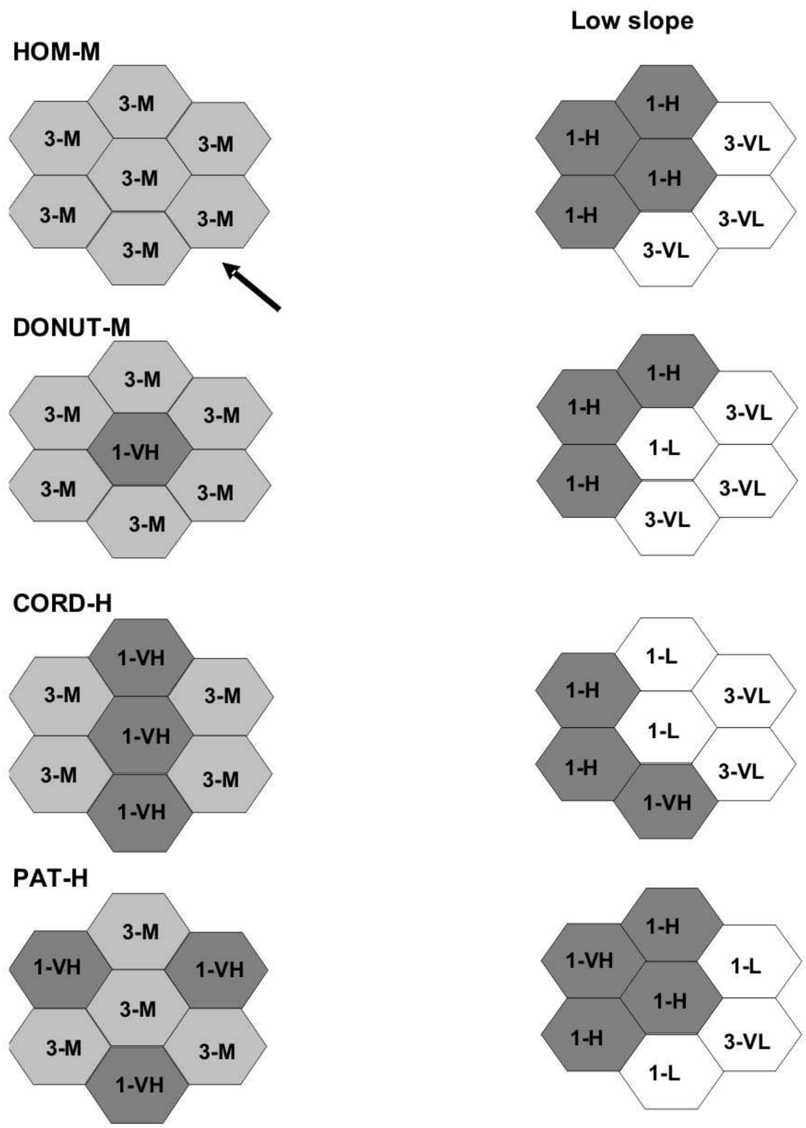
Actions			
cut = harvest	cut&fuel = harvest and fuel treatment	fuel = fuel treatment	grow = grow only

FIGURE 5.58: Optimal decisions for different southeast slope steepness (labeled "action")



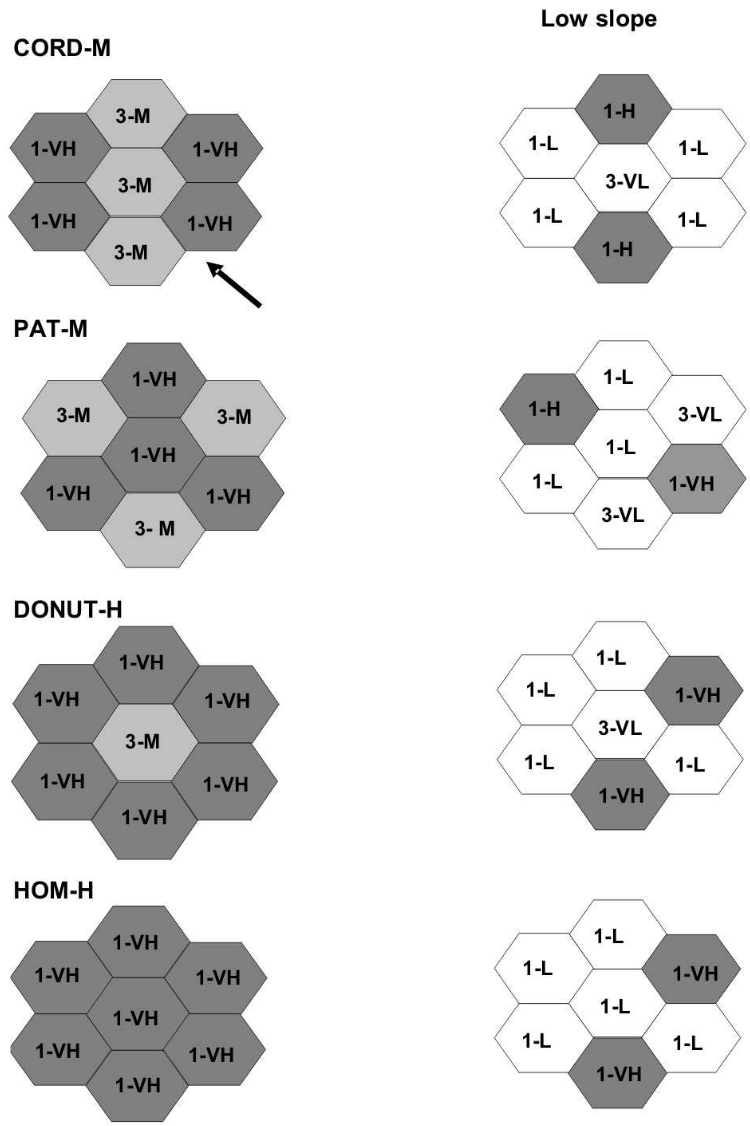
Actions			
cut = harvest	cut&fuel = harvest and fuel treatment	fuel = fuel treatment	grow = grow only

FIGURE 5.59: Optimal decisions for different southeast slope steepness (labeled ”action”)



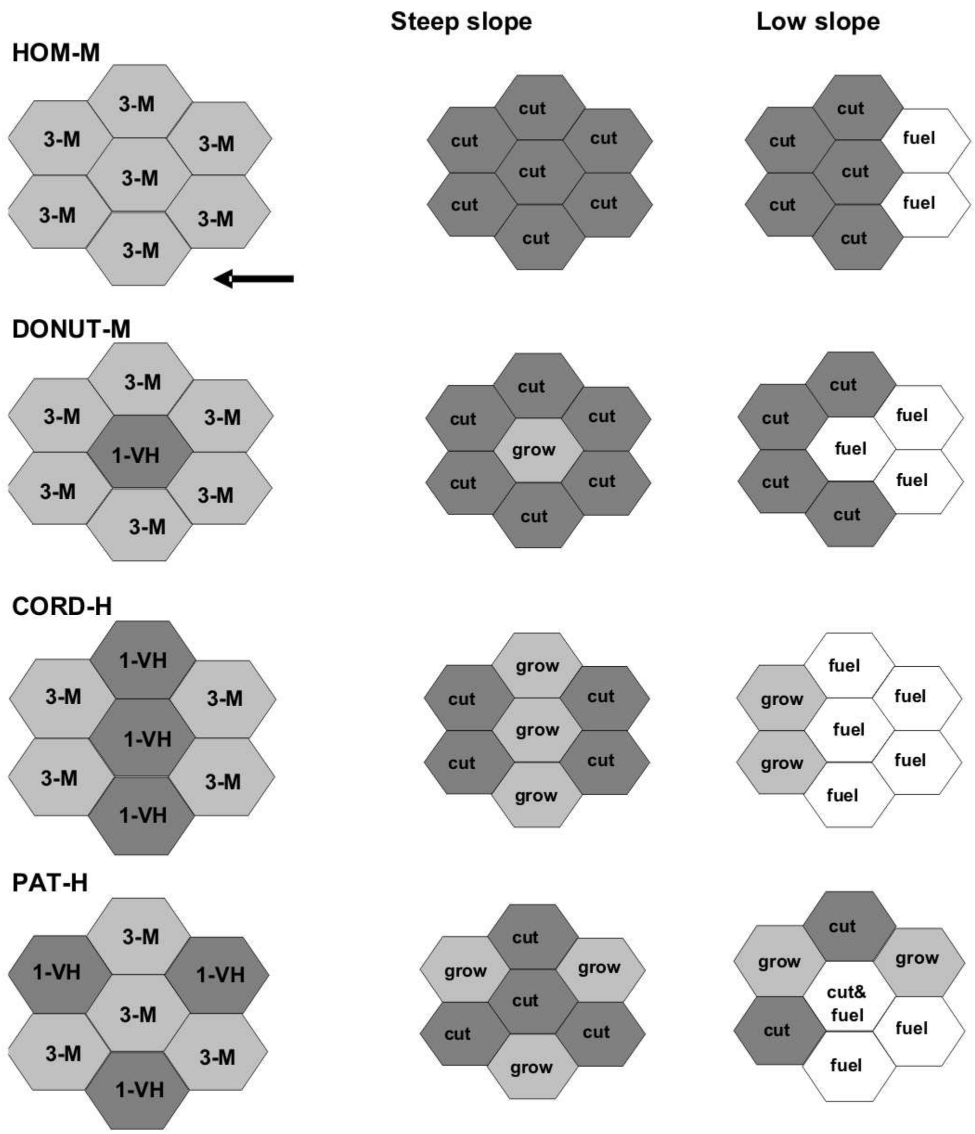
Fuel Condition Class				
VL = Very Low	L = Low	M = Medium	H = High	VH = Very High

FIGURE 5.60: Optimal landscapes for different southeast slope steepness after optimal decision is applied (labeled "age class - fuel condition")



Fuel Condition Class				
VL = Very Low	L = Low	M = Medium	H = High	VH = Very High

FIGURE 5.61: Optimal landscapes for different southeast slope steepness after optimal decision is applied (labeled "age class - fuel condition")



Actions			
cut = harvest	cut&fuel = harvest and fuel treatment	fuel = fuel treatment	grow = grow only

FIGURE 5.62: Optimal decisions for different east slope steepness (labeled "action")

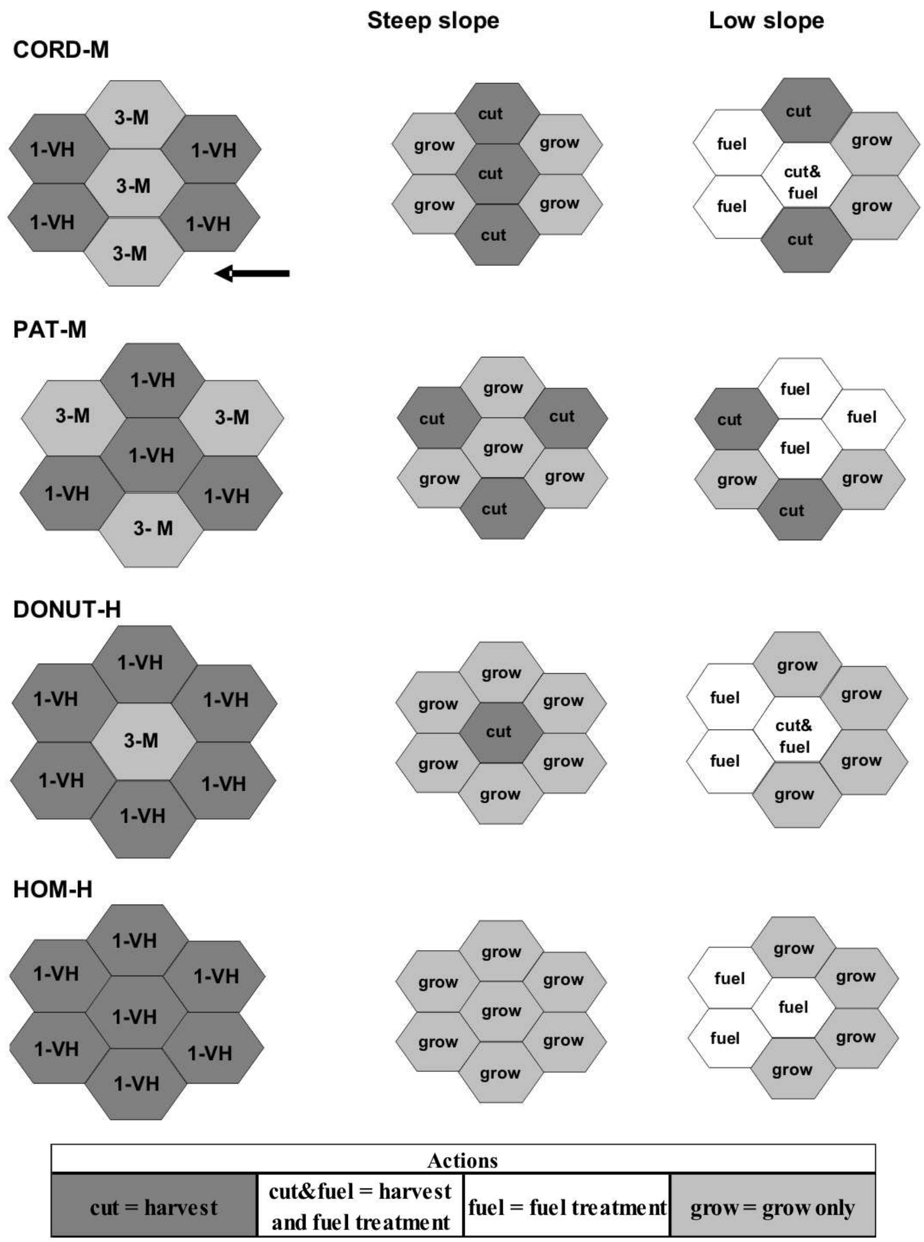
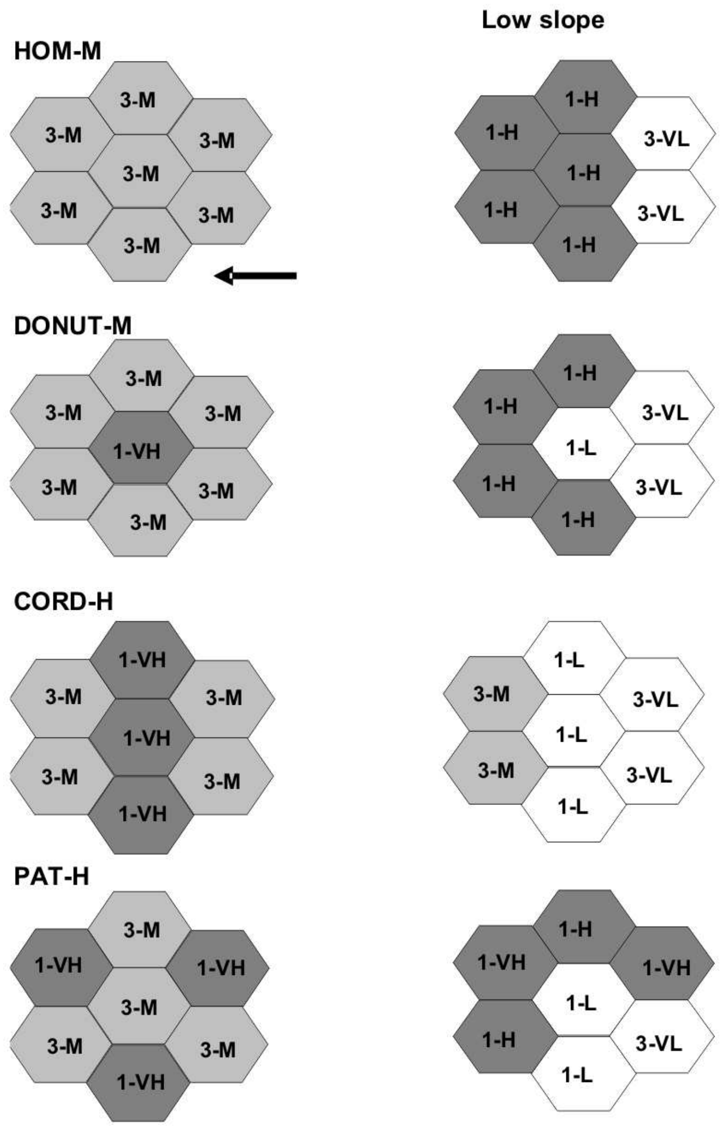
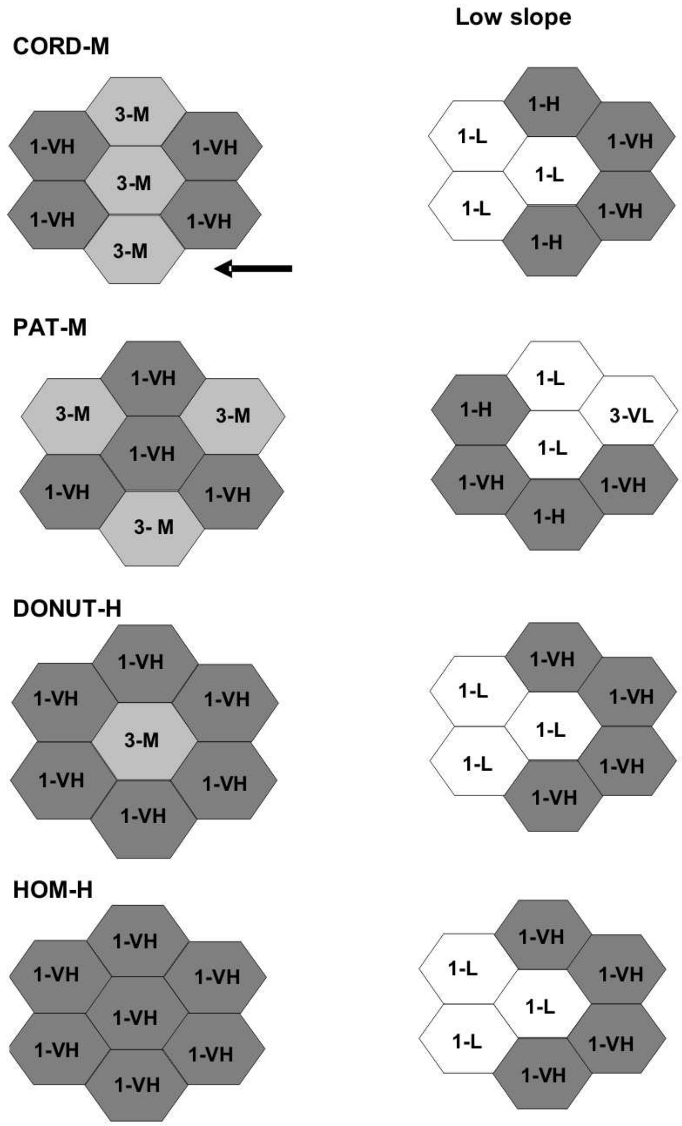


FIGURE 5.63: Optimal decisions for different east slope steepness (labeled ”action”)



Fuel Condition Class				
VL = Very Low	L = Low	M = Medium	H = High	VH = Very High

FIGURE 5.64: Optimal landscapes for different east slope steepness after optimal decision is applied (labeled "age class - fuel condition")



Fuel Condition Class				
VL = Very Low	L = Low	M = Medium	H = High	VH = Very High

FIGURE 5.65: Optimal landscapes for different east slope steepness after optimal decision is applied (labeled "age class - fuel condition")

6. DISCUSSION AND CONCLUSIONS

Because investment decisions about fuel treatment must be made prior to a fire event, land managers must consider the possible effects of fuel treatments on spatial patterns of fire damage. Because fires spread over space depending on fuel conditions, an action taken in an MU affects the risk of value losses by fire damage in both that MU and in adjacent MUs - affecting the spatial endogenous risk. Therefore, in order to incorporate the spatial fire process in the search for an efficient spatial allocation of fuel treatments, I have developed a framework that explicitly addresses spatial endogenous risk - the risk of values losses by fire damage that depends on spatial allocation of actions - which captures a spatial externality - one MU's condition partly determines the risk of value loss on all other MUs. My framework integrates a stochastic dynamic optimization model with a fire simulation model, which depicts spatial patterns of fire spread based on the principle commonly used by fire scientists. Consideration of spatial endogenous risk requires a departure from the conventional stand-level or non-spatial model, which is often used for analytical tractability.

Although, the problem becomes analytically intractable and, therefore, requires numerical solutions, my framework addresses a complex decision making process involving different spatial allocations of management effort - fuel treatment and harvest – to address risks of fire. Also, my framework captures the effects of a spatial externality on cost effective spatial allocations of fuel management.

In Chapter 4, numerical solutions for a particular set of economic and physical parameters are used to illustrate several important issues in implementing efficient fuel treatments over a landscape. In Chapter 5 sensitivity analyses are described to investigate various physical and economic parameters and their impact on management decisions. These results confirm that the results in chapter 4 hold under various economic and physical environments with exceptions.

In the following section, some of the main themes developed in this study are discussed.

6.1. Effects of Spatial Externality on Decisions

In chapter 4, management decisions for 25 different initial spatial configurations indicate that negative externalities between MUs make it optimal to separate MUs with high spread rates. This "separation strategy" limits the spread of fire with the treated MU, creating a positive spatial externality by limiting risk to other MUs. This economic analysis provides supports for the separation strategy that has been suggested by many wildfire scientists [46].

In order to investigate the effect of a spatial externality on the rotation age, I compare the impact of risks - "threshold risk levels"- for an aspatial problem and for a spatial problem. The higher a threshold risk level is, the more likely the land manager will choose to hold timber rather than harvest. The effect of fire risk in a spatial model is more complex than in a single-stand model. The results show that if spatial externalities are considered, rotation age is shortened less and may even be lengthened because there is a trade-off between the risk of value loss by fire damage in near mature MUs and the effect of harvesting these MUs on adjacent MUs. As opposed to the study by Reed [5], the results indicates that a spatial externality does not necessarily shorten the optimal rotation age because compared to MUs that have been recently harvested, MUs that contain a standing forest will lower the risk of fire in adjacent MUs.

The sensitivity analysis reveals another interesting effect of a spatial externality. According to well established economic theory an increase in the discount rate will shorten the optimal rotation age. However, because harvesting an MU can increase the spread rate of fire and increase the risk of fire damage in adjacent MUs, harvesting strategies in a spatial framework are heterogeneous within age classes - that is, not all MUs of the same age class are optimally harvested at the same time. This result comes from moving beyond an analysis of only one MU toward an analysis of spatial interactions of fire movement and spatial externalities in risk. These results indicate that information about risk from a conventional stand level problem will be less useful, and often misleading, in cases where land units interact across space and landscape management is necessary.

6.2. On-site Value Protection and Prevention of the Spread of Fire

Both the base case analysis in chapter 4 and the sensitivity analysis in chapter 5 show that there are spatially explicit trade-offs that a land manager faces in deciding the optimal spatial allocation of fuel management efforts. A land manager faces trade offs between protection of on-site value (protection of valuable MUs) from fire and prevention of fire spread (treatment of MUs with high spread rates). A land manager generally has more incentive to assign fuel treatment to valuable MUs because of the higher benefits of protection of these valuable MUs. However, because the spread of fire causes a significant value loss, a land manager treats the "source" of a fire spread. If MUs with high spread rates are left untreated, fire that ignites from these MUs burns multiple MUs and often leads to a significant loss of values. For that reason, treating MUs with high spread rates, which are often not valuable, may be optimal. One decision will dominate the other depending on initial spatial configurations and parameter values used. For example, in a certain physical environment where a single ignition does not result in a significant value loss by fire damage in multiple MUs, a land manager will be better off focusing his or her management efforts on protection of on-site value.

6.3. The Center MU

Disconnecting MUs with high spread rates and limiting the spread of fire in multiple MUs make the center MU particularly valuable for risk reduction. With a limited budget, the center MU typically gets a high priority for fuel treatment. The importance of protecting the center MU can be quantified as the "spread protection value", which is how much the expected NPV increases from protection of a single MU. This marginal value of fuel treatment is a function of initial spatial configurations. Therefore, as chapter 5 shows, the cost of fuel treatment which is offset by marginal expected NPV varies depending on landscapes. Although it is important to treat the center MU, because of the spatially explicit trade-offs described above, the center MU is not optimally treated in situations when the center MU has fuel condition of medium spread rate and MUs with high spread rates are separated without treating the center MU.

6.4. Heterogeneous Risk over Homogenous Landscape

Chapter 5 shows that factors such as winds and slopes generate heterogeneous risks over a homogenous fuel landscape due to the spread of fire. Introducing slopes makes a landscape heterogeneous in topographic conditions. Because the rate of fire spread depends on the direction of slope, MUs at the bottom of a slope produce spatial risk, which generates a heterogeneous risk surface over a homogeneous fuel landscape (fire moves upslope).

Introducing prevailing winds to the model generates a heterogeneous risk in a completely homogenous landscape (in terms of both fuel and topographic conditions) because fire that ignites in upwind MUs spreads to downwind MUs. Therefore, different actions are taken in MUs of the same age class and fuel conditions over a homogeneous landscape when factors such as winds and slopes affect fire growth and behavior. These results highlight the importance of using a spatially explicit model to find optimal fuel management allocations not only because there is an interesting behavioral response over a heterogeneous landscape but also because external factors (winds and slopes) generate a heterogeneous risk surface on a homogenous fuel landscape, which cause non-homogenous actions over space.

6.5. "Rule of Thumb" Strategies

Although "rule of thumb" strategies that do not take into account a spatial process are often suboptimal because important spatial interactions are overlooked, the optimal strategy generated from a spatially explicit model can be no different from a "rule of thumb" strategy when a spatial process does not produce spatial risk. A spatial explicit model provides an insightful framework which allows a land manager to search the optimal decision by fully taking into account spatial interactions when a spatial process produces spatial risk and it affects the action in each MU. It is likely that "rule of thumb" strategies over- or under- protect the landscape or spatially misallocate fuel treatment when spatial risk affects the action taken in each MU.

In Chapter 4 "rule of thumb" strategies that ignore spatial component are compared with the optimal decision that fully takes into account spatial externality. Because implementing a fully spatial model can be costly or information intensive, the comparison of management plan with and without spatial components identifies situations in which the aspatial model is a good approximation versus when it is particularly costly. The results show that second best solutions ("rule of thumb" strategies) such as protection of all valuable MUs or protection of all MUs with high spread rates will deviate from the optimal strategy in important ways when 1) a "rule of thumb" strategy leaves connected multiple MUs of high spread rates untreated and, 2) failing to treat valuable MUs lowers the expected NPV. The results demonstrate that when a land manager ignores spatial aspects of decisions, he or she may over- or under- protect the landscape, or spatially misallocate fuel treatment.

However, sensitivity analyses in chapter 5 indicate that in a certain physical environment, the "rule of thumb" strategy can be almost as good or even as good as the optimal decision. For example, when fire duration is short, fire does not spread to adjacent MUs. In this case, leaving connected multiple MUs with high spread rates will mean that second best decisions will be comparable to the optimal decision. Also, for example, when fuel treatment is effective at the MU level due to, for example, mild weather conditions, a land manager focuses his or her management efforts on protecting on-site value. In this case, because a land manager treats all valuable MUs, second best solutions will not be different from the optimal decision.

6.6. Effects of Winds or Slopes on Strategy for "Target" Fire

Because factors such as winds and slopes can narrow the range of possible fire patterns, developing a strategy can be an easy task and can be a good approximation for the optimal strategy when these factors are not extreme but have a significant impact on fire growth and behavior. In Ch.4, I compare the strategy generated for a particular fire size and shape and the strategy for unknown fire patterns. This comparison is conducted because some researchers have developed a framework to find the optimal decision for an anticipated fire pattern. They use a particular fire size and shape, which is called a "target" fire, and find the optimal decision based on the prediction that this "target" fire will occur. The results show that the optimal decision for the "target" fire is efficient only when the "target" fire occurs. Management cost can be high if the "target" fire is just one of many possible fires because the "strategy" generated for a "target" fire yields a lower value in a situation where all possible fire patterns are considered. The results in Section 4.5 show that the strategy generated for the "target" fire yields the lower objective value by $1,350 / acre compared with the strategy for unknown fire patterns. This possibly high cost results from a wide range of possible fire patterns. In chapter 5, outputs from fire simulation runs indicate that fewer possible spatial fire patterns may result from random ignition locations when abiotic (i.e. winds and slopes) factors influence fire growth and behavior significantly. A prevailing wind direction may make ignitions from any upwind (or downwind) MU result in a single fire pattern. Then, if a land manager knows this prevailing wind direction, developing a strategy for the "target" fire becomes a relatively easy task. However, sensitivity analyses also show that when the prevailing wind is strong, spatial layout of fuel treatment becomes ineffective for mitigating the risk of fire damage. These results are consistent with previous findings of wildfire scientists.

6.7. "Myopic" and "Foresighted" Land Managers

Land managers who consider the role of forthcoming information in current decisions tend to assign less fuel treatments than those who do not. A "foresighted" land manager values flexibility to adjust decisions and uses a closed loop decision framework. A "myopic" land manager does not consider the possibility of adjusting decisions in response to forthcoming information when he or she makes the current decision and uses an open loop decision system. Differences in optimal decisions arise when forthcoming information is valuable as in the case when future price depends on the amount of timber harvested so that the more MUs burned, the higher the stumpage price becomes. This price change makes alternative harvesting patterns attractive in the event of fire and makes the expected value of information positive.

The results show that a "myopic" land manager might overreact to the risk of fire loss because he or she ignores the possibility of adjustments when making decisions. For a "foresighted" land manager, price changes will increase the value of harvest and will help a "foresighted" land manager to mitigate a loss of value in the event of fire by making an alternative harvesting pattern available. My framework generates efficient solutions by allowing a land manger to adjust decision depending on forthcoming information. In conditions under which this approach is appropriate, my results support an adaptive management framework that has been suggested by many scientists [67].

6.8. Extensions

Considering broader definitions of benefits and costs associated with fuel treatment could provide useful extensions to this work.

When timber can be salvaged from a damaged MU, a land manager can obtain some value proportional to the original value that he or she could have obtained if not fire had occurred. In this setting, I can compare the optimal decision (assignment of fuel treatment) between a case where salvage logging is permitted and a case where it is not. A land manager undertakes less fire prevention and fuel management if salvage logging mitigates the loss of associated fire.

The issues of post-logging regeneration on future values imply that two different states after salvage logging will lead to dramatically different management strategies. If after salvage logging the risk of future fire spread increases, then the optimal strategy might be to refrain from salvage logging and to give up the revenue from salvageable timber in exchange for a lower risk of fire. If the risk of fire damage decreases or does not change after salvage logging, then the optimal strategy involves salvage logging after fire.

The spatial issue in this case is whether or not salvage logging generates a spatial externality. If it generates a spatial externality, then it is important to find out how to fully take into account the associated cost. If a land manager can lower the risk of fire that spreads from a fire damaged MU after salvage logging by treating adjacent MUs, and values obtained from salvage logging is high enough to offset the risk of value loss in adjacent MUs, then he or she will be better off by salvaging damaged timber.

In order to model these two states and decisions including the action of salvage logging in this context, a two period model has to be extended to longer time frame so that descriptions of states after salvage logging are meaningful. For example, the current period decision depends upon fire events after both the current period's decision and the second period's decision involving salvage logging. This model clearly increases the state space, which will increase computational time significantly.

Broader possible actions including fire suppression efforts might allow us to measure the benefits of fuel treatment in terms of reducing the cost of suppression efforts. It also makes a land manager's decisions more flexible and realistic because the risk of fire loss can be lowered by both proactive and reactive actions. Often the public sector is responsible for fire suppression efforts, while fuel treatment can be conducted by both the public and private sectors. I can model this issue as a problem for two agencies, where suppression efforts will be conducted by one agency (public) and fuel treatment will be conducted by the other (private). A game theoretic approach might be useful for this kind of study. I might be able to see, for example, how the optimal spatial allocation of fuel management changes if private landowners know that in the event of fire, the public sector will provide suppression efforts.

The effectiveness of suppression efforts is a function of prevention efforts. If a land manager knows that suppression efforts will be provided by a public agency and knows how effective the suppression effort will be, then he or she might decide to invest less on fire prevention efforts and fuel management. The decision as to how much to invest on fuel management will probably depend on the effectiveness of suppression efforts. In this case, spatial issues will address which fire pattern will increase or decrease the effectiveness of suppression efforts. It might be possible to find the spatial fire pattern resulting from a particular spatial allocation of fuel treatment, which will allow an agency to effectively suppress fire.

While the private sector often values only the financial aspects of forest resources, the public sector values the multiple attributes of forest resources and manages forests for multiple objectives including intangible objectives such as ecosystem health and habitat for wildlife. Because of these ecological objectives, fuel management in public forests is often excluded. But exclusion of these activities from public lands might impose fire risk not only in public forests but also in adjacent lands owned by private land owners who have no restrictions on conducting fuel treatment. It would be interesting to use this framework to evaluate how costly it is to manage public land when management activities on this land increase the risk of fire on private land. The results here suggest that a consideration of a spatial externality might lead to a change in management strategies on public lands by allowing some active management in critical MUs that are adjacent to a private land.

Although tradeoffs between wildlife and timber production have been studied [68] [69], little is known about the impact of fire on these trade-offs. The framework developed here can be used to illustrate tradeoffs between protection of suitable habitat and the risk of fire damage and its effect on habitat as well as tradeoffs between timber production and habitat quality. Habitat for wildlife often requires connectivity of suitable habitat as an indicator of habitat quality [70]. Because my framework utilizes a spatially explicit model, this kind of spatial indicator could be easily computed and evaluated. I can model both timber production and habitat for wildlife under the risk of fire using this framework. The requirement of connectivity of suitable habitat often restricts activities including mechanical thinning and prescribed burning on some locations. Therefore, the risk of fire in some MUs might increase. Possible spatial allocations of fuel management efforts might be inefficient because of this additional spatial constraint.

Because under current policy harvesting (clear cutting) will rarely be an option in national forests because of ecological objectives, and because fuel treatment has received increasing interest as a way of mitigating the risk of fire loss, it would be interesting to evaluate the options of different fuel management intensity levels with different costs. Instead of harvesting, I can include different intensive fuel treatments and can evaluate how a land manager assigns high intensity fuel treatment at a higher cost and low intensity fuel treatment at a lower cost. This model can tell us what the optimal mix (if any) is of these two different treatments and what the optimal spatial allocation is of these two activities across a given landscape. This model can demonstrate tradeoffs between implementing low intensity fuel treatments over a large area and implementing high intensity fuel treatments in a limited area. Because there is a limited budget for fuel treatment and there are many areas which require immediate treatment, it is important to answer the question of how agency should allocate their limited resources to mitigate the risk of fire. When and where is it better to treat a broader area with low intensity strategies or treat a limited area with high intensity strategies?

Evaluating mechanical thinning in terms of both fuel reductions and a financial return is an important issue because only a few fuel treatments have been conducted due to the limited budget for fire management. If fuel treatment can pay for itself, there is a greater chance that fuel treatment will be conducted. Because studies suggest that implementing commercial thinning does not mitigate the risk of fire, there have been several studies on how thinning for fuels reduction generates financial flow. However, there have been few studies conducted within the context of spatially explicit and inter-temporal decisions under the risk of fire. Using my framework, I can take into account the different risk levels that might occur after implementation of a spatial allocation of different thinning operations. Addressing different risk levels is important because in the process of finding the optimal decision about thinning a land manager makes trade-offs between risk of value losses, cost and revenue of thinning.

Lastly, I can also extend my framework to other issues related to the risk of fire, in particular, invasive species that spread as a function of fire. Cheatgrass is known as an invasive species that both increases fire risk and establishment after fire [71] [72] [73]. Cheatgrass has replaced native shrub species following fire and has resulted in the loss of significant sagebrush steppe habitat [74]. Therefore, a land manager has an incentive to lower the risk of fire damage and also lower the risk of the damage from cheat grass. Controlling cheat grass will not only lower the risk of damage from cheat grass but also the risk of fire. My framework can be extended to find the optimal investment level for the prevention of cheat grass and the optimal spatial allocation for prevention efforts. A three or longer period model would be desirable because at the end of current period, if control of cheatgrass has not been successful, the risk of fire damage will increase in the second period, which in turn will increase the chance of establishment and spread of cheatgrass. This dynamic and spatial process could lead a land manager to invest more on prevention efforts in the current period. Although, invasive species problem have been extensively studied [31] [32] [33] [34] [75], there have been only studies accounting for spatial interactions explicitly. Use of this framework will illustrate how spatial allocations of management efforts will respond to the risk of cheatgrass establishment and spread over space and benefits from prevention efforts.

6.9. Concluding Remark

As economists have become aware of the importance of modeling spatial interactions for both biological (e.g. connectivity of habitat) and economic (e.g. behavior over space in response to relative value) reasons, they have begun to incorporate spatial aspects of decisions and biological systems into their analyses. However, economists have rarely modeled spatial risk or situation in which spatial risk are traded-off against costs of management efforts. Meanwhile, emerging biological evidence indicates that stochasticity has to be considered in order to address important dynamic process of a system as well as spatial interaction. The framework I developed here addresses both spatial and stochastic components of a system within a dynamic decision making framework and can be used to answer important economic questions such as: 1) what does a cost effective spatial allocation of fuel management efforts under uncertainty look like? 2) what spatially explicit trade-offs does a land manager face when risks of value losses by fire can also be traded off against treatment costs and benefits of harvest? and 3) how the optimal decision under uncertainty responds to various physical and economic circumstances?

The contribution of this study to resource economics literature is in providing a framework that can be used to answer these questions and revealing important insights for implementing efficient spatial allocation of fuel management. Although this framework requires a considerable amount of computational effort in terms of time, capacity and skills, future advances in computer technology will enable us to more easily solve this kind of problem as well as more complicated problems. Nonetheless, insights from the stylized model can inform policy.

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APPENDICES

A APPENDIX Fire Growth Equations

To predict the spread of fire for given initial fuel conditions, weather types and ignition points, the program based on Huygens' principle of wave propagation [12], which is commonly used in fire behavior models such as FARSITE [11], is programmed. Huygens' principle assumes that each vertex can serve as the source of an independent elliptical expansion [11]. The dimensions of an elliptical wave were calculated using a steady-state spread rate, R (m/min). 360 points were expanded using the equation developed by Richards [49]:

$$xt = \frac{a^2 \cdot \cos\theta(xs \cdot \sin\theta + ys \cdot \cos\theta) - b^2 \cdot \sin\theta(xs \cdot \cos\theta - ys \cdot \sin\theta)}{(b^2 \cdot (xs \cdot \cos\theta - ys \cdot \sin\theta)^2 + a^2(xs \cdot \sin\theta + ys \cdot \cos\theta)^2)^{1/2}} + c \cdot \sin\theta \quad \text{(A.1)}$$

$$yt = \frac{-a^2 \cdot \sin\theta(xs \cdot \sin\theta + ys \cdot \cos\theta) - b^2 \cdot \cos\theta(xs \cdot \cos\theta - ys \cdot \sin\theta)}{(b^2 \cdot (xs \cdot \cos\theta - ys \cdot \sin\theta)^2 + a^2(xs \cdot \sin\theta + ys \cdot \cos\theta)^2)^{1/2}} + c \cdot \cos\theta \quad \text{(A.2)}$$

where: xt, yt: time derivative of x-y coordinates

xs, ys: xs = $(\mathrm{x}_{j-1} - \mathrm{x}_{j+1})$ +- D_i*sinω_i

ys = $(\mathrm{y}_{j-1} - \mathrm{y}_{j+1})$ +- D_i*cosω_i

where: ω_i is the aspect of ith vertex. D_i is called as a slope correction.

$$Di = \left[(x_{i-1} - x_{i+1})^2 + (y_{i-1} - y_{i+1})^2\right]^{1/2} \cdot \cos\delta_i \cdot (1 - \cos\phi_i) \quad \text{(A.3)}$$

where: i is the local slope of ith vertex.

In the case of a flat landscape xs = $(\mathrm{x}_{j-1} - \mathrm{x}_{j+1})$, ys = $(\mathrm{y}_{j-1} - \mathrm{y}_{j+1})$.

a: f1(R, U), a is an increasing function of R (see Appendix B) and U, where U is wind speed, and defined as:

a=0.5*(R+R/HB)/LB

where LB: LB=0.936$e^{0.2566U}$+0.461$e^{-0.1548U}$-0.397

HB: HB=(LB+(LB^2-1)$^{0.5}$)/(LB-(LB^2-1)$^{0.5}$)

b: f2(R), b is an increasing function of R and defined as:

b=(R+R/HB)/2

c: f3(b, R), c is an increasing function of R and defined as:

c=b-R/HB

θ: $\theta = \tan^{-1}((\tan(\omega i) - \tan(\text{wind\_direction}))/\cos(\text{slope}))$.

B APPENDIX Spread Rate

The heading surface fire steady-state spread rate, R, is based on the equation developed by [78]. The equation assumes that fire spreads by a sequence of ignitions. Rothermel's equation is defined as follows:

$$R = \frac{I_R \cdot \xi \cdot (1 + \phi_w + \phi_s)}{\rho_b \cdot \varepsilon \cdot Q_{ig}} \tag{B.1}$$

where:

R: rate of spread,

I_R : reaction intensity, the measure of the energy release rate per unit area of combustion zone

ξ : propagation flux ratio, the proportion of the total heat produced in the combustion zone

ϕ_w: wind coefficient

ϕ_s: slope coefficient

ρ_b : ovendry bulk

ε : effective heating number

Q_{ig} : heat of pre-ignition

Rothermel further modified Eq.[B.1] to accept fuels that were composed of heterogeneous mixtures of fuel types and particle size by using the weighting parameters based on the surface area of the fuel within each size class and category (live fuel or dead fuel).

C APPENDIX Fuel Characteristics Table

Fuel Model(FM) (Source)	Fuel Type	Dead Fuel						Living Fuel		Fuel Depth (meter)
		fine (1-hour)		medium (10-hour)		large (100-hour)				
		σ	wo	σ	wo	σ	wo	σ	wo	
FM 6 (Anderson, 1982)	very high	5742	0.3370	358	0.5605	98	0.4484	4922	0.4492	0.762
FM12 (Anderson, 1982)	high	4922	0.8988	358	3.1445	98	3.7060	0	0.0000	0.70104
FM9 (Anderson, 1982)	medium	6562	0.6738	358	0.4492	98	1.1230	4922	0.4492	0.3048
FM 17 (Stephens, 1998)	low	6562	0.2013	358	0.1121	98	0.0000	4922	0.2466	0.1524
FM 15 (Stephens, 1998)	very low	8203	0.7622	358	0.0897	98	0.0448	0	0.0000	0.1524

σ : surface to volume ratio (/m)

ω_0 : loading (kg/m^2)

D APPENDIX Source Codes - Stochastic Dynamic Programming

```
#include <stdio.h> \\
#include <stdlib.h> \\
#include <time.h> \\
#include <math.h> \\
#include <string.h> \\
#include <malloc.h> \\
#include <iostream.h> \\
#include <FLOAT.H> \\

//#define MU 7
#define MU 7
//#define PATTERN 128
#define PATTERN 128
#define DECISION 16384
#define AGE 11
#define PRICE 500
#define COST_H 200
//#define COST_H 290//600
//#define COST_H 250
//#define COST_H 320
//#define COST  233
//#define COST  250
```

```
//#define COST  185
//#define COST  200  // fuel cost original!!!
#define COST  1000 #define REG_COST 150 // original
//#define REG_COST 300
#define INTEREST 0.04
//#define SEV  1240000
//#define SEV  0
//#define INTEREST 0

int **imatrix( unsigned long rows, unsigned long columns); \\
float **fmatrix( unsigned long rows, unsigned long columns); \\
double **dmatrix( unsigned long rows, unsigned long columns);

void freefmatrix( unsigned long rows, unsigned long columns, float
**fmatrix); \\
void freeimatrix( unsigned long rows, unsigned long
columns, int **imatrix);


/*------------------------------------------------------------------------*/
//int main()
int main(int numParam, char *param[]) {
    int     r, c, temp, p, stand_age, best_dec, stand_age02, \\
            best_dec02, counter, fuel_counter;\\
    int     i, pe, w, f, j, k, ig_pt, weather, m, n, dec01, \\
```

```
            dec02, state, pattern, decision; \\
    float   sum, ftemp, objective0, current_pnw, pnw, best_pnw,\\
             vol_01, pnw02, opt_value02; \\
    float   current_pnw02_exp, best_pnw02_exp, vol_02, \\
            prob_p, expect_f; \\
    float   discount_factor, SEV;
//  int     stands[STAND];  //allocate # of stands.

//  float   norm_prob_finl02[DECISION][PATTERN];
//  float   prob_finl02[DECISION][PATTERN];

    char fileName[100];

    FILE    *inFile, *outFile, *fp_out;

    int **dec;
    int **init_cond;
    float   **vol;
    int    **per02_age;
    int **per02_fuel;
    float **prob;
    int    **opt;
    float   **opt_value;
    float  **sevValue;
```

```
//  opt[state] = best_dec;
//  opt_value[state] = best_pnw;

    prob = fmatrix(DECISION, PATTERN);
    dec = imatrix(DECISION, MU);
    init_cond = imatrix(MU, 2);
    vol = fmatrix(AGE, 2);
    per02_age = imatrix(PATTERN*DECISION, 2);
    per02_fuel = imatrix(PATTERN*DECISION, 2);
    opt = imatrix(PATTERN*DECISION,2);
    opt_value = fmatrix(PATTERN*DECISION,2);
    sevValue = fmatrix(5,2);

    if(numParam != 6)
    {
        puts("Usage: createOutFile<inputFile> <inputFile>
                <inputFile> <outFile>\n");
        exit(0);
    }

/*------------------READ FILE----------------------*/

    inFile = fopen("4actions_comb.prn", "r+");
//  inFile = fopen("decisions.prn", "r+");
    if(inFile == NULL )
```

```
    {
        cout << "decision was not opened." << endl;
        exit(0);
    }
    else
    {
        for ( r = 0; r < DECISION; r++ )
        {
            for( c = 0; c < MU; c++)
            {
                fscanf(inFile, "%d", &dec[r][c]);
            }
        }
    }
    fclose(inFile);

    printf("dec = %d\n", dec[0][1]);

    inFile = fopen(param[1], "r");
//  inFile = fopen("init_fuel_10_01_cond.prn", "r+");
//  inFile = fopen("init_fuel_01_02_cond.prn", "r+");
    if(inFile == NULL )
    {
        cout << "init_cond was not opened." << endl;
        exit(0);
```

```
    }
    else
    {
        for ( r = 0; r < MU; r++ )
        {
            for( c = 0; c < 2; c++)
            {
                fscanf(inFile, "%d", &init_cond[r][c]);
            }
        }
    }
    fclose(inFile);

    printf("init_cond = %d\n", init_cond[0][1]);



//  inFile = fopen("ig_we_prob_alldec01.prn", "r+");
//  inFile = fopen("may26_03_volume.prn", "r+");
//  inFile = fopen("aug15_volume01.prn", "r+");
    inFile = fopen("july21_volume02.prn", "r+");
    if(inFile == NULL )
    {
        cout << "volume was not opened." << endl;
        exit(0);
```

```
    }
    else
    {
        for ( r = 0; r < AGE; r++ )
        {
            for( c = 0; c < 2; c++)
            {
                fscanf(inFile, "%f", &vol[r][c]);
            }
        }
    }
    fclose(inFile);

    inFile = fopen(param[2], "r");
//  inFile = fopen("per02_age_finl_aug27_10_01.prn", "r+");
//  inFile = fopen("per02_age_finl_aug27_01_02.prn", "r+");
    if(inFile == NULL )
    {
        cout << "per02_age was not opened." << endl;
        exit(0);
    }
    else
    {
        for ( r = 0; r < PATTERN*DECISION; r++ )
        {
```

```
            for( c = 0; c < MU; c++)
            {
                fscanf(inFile, "%d", &per02_age[r][c]);
            }
        }
    }
    fclose(inFile);



    inFile = fopen("per02_fuel_finl_aug08_00_00.prn", "r+");
//  inFile = fopen("per02_fuel_finl_aug27_10_01.prn", "r+");

    if(inFile == NULL )
    {
        cout << "per02_fuel was not opened." << endl;
        exit(0);
    }
    else
    {
        for ( r = 0; r < PATTERN*DECISION; r++ )
        {
            for( c = 0; c < MU; c++)
            {
                fscanf(inFile, "%d", &per02_fuel[r][c]);
            }
```

```
        }
    }
    fclose(inFile);

    inFile = fopen(param[3], "r");
//  inFile = fopen("norm_prob_01_newest_02.txt", "r");
//  inFile = fopen("aug21_norm_prob_10_newest_02.txt", "r");
        if(inFile == NULL)      exit(-5);

    for(r = 0; r < DECISION; r++)
    {
        for(c = 0; c < PATTERN; c++)
            fscanf(inFile,"%f\t", &prob[r][c]);
    }

    fclose(inFile);

    inFile = fopen("opt.txt", "r+");
//  inFile = fopen("opt.prn", "r+");
    if(inFile == NULL )
    {
        cout << "per02_fuel was not opened." << endl;
        exit(0);
    }
    else
```

```
{
    for ( r = 0; r < PATTERN*DECISION; r++ )
    {
        for( c = 0; c < 2; c++)
        {
            fscanf(inFile, "%d", &opt[r][c]);
        }
    }
}
fclose(inFile);



inFile = fopen("opt_value.txt", "r");
if(inFile == NULL)        exit(-5);

for(r = 0; r < PATTERN*DECISION; r++)
{
    for(c = 0; c < 2; c++)
        fscanf(inFile,"%f\t", &opt_value[r][c]);
}

fclose(inFile);

inFile = fopen(param[4], "r");
//  inFile = fopen("sev.txt", "r");
```

```
//   inFile = fopen("aug21_norm_prob_10_newest_02.txt", "r");
          if(inFile == NULL)          exit(-5);

     for(r = 0; r < 5; r++)
     {
          for(c = 0; c < 2; c++)
               fscanf(inFile,"%f\t", &sevValue[r][c]);
     }

      fclose(inFile);



/// START SDP ///////////////////////////////////////////
best_pnw = 0.0; best_pnw02_exp = 0.0; discount_factor =
1/(pow((1+INTEREST), 10));
     printf("discount_factor is: %f\n", discount_factor);

     counter = 0;

fp_out = fopen(param[5], "w");

//Second stage optimization:
for (state=0; state < PATTERN*DECISION; state++)
//for (state=0; state < PATTERN; state++)
{
```

```
best_pnw = -4000000.0;
best_dec = 0;

if(state == 224896)
     state = state;



for(dec01=0; dec01 < DECISION; dec01++)
{
     if(dec01 == 16383)
          dec01=dec01;

     current_pnw = 0.0;

     pnw = 0.0;

     SEV = 0.0;

     stand_age = 0;

     for(j=0; j<MU; j++)
     {
          stand_age = per02_age[state][j];
```

```
        if(stand_age == 0)
            pnw -= REG_COST;
//      if(stand_age != 4)
//          stand_age = stand_age;
      //find the best one
        if( dec[dec01][j] == 1 )  // cut and no fuel treat
        {
        //  stand_age = per02_age[state][j];

                //init_cond[j][0];
            vol_01 = vol[stand_age][1];

          //  SEV = SEV_40;
             SEV = sevValue[4][1];

        //  pnw += SEV/(pow((1+INTEREST), 10));

            pnw += vol_01*PRICE*discount_factor -
                COST_H*discount_factor + SEV;

        }
        else if(dec[dec01][j] == 2)  // cut and fuel treat
        {

        //  stand_age = per02_age[state][j];
```

```
          //init_cond[j][0];
        vol_01 = vol[stand_age][1];

//   SEV = SEV_40;
        SEV = sevValue[4][1];

        pnw += vol_01*PRICE*discount_factor -
            COST_H*discount_factor -
            COST*discount_factor + SEV;
        //pnw -= COST*discount_factor;

}
else if(dec[dec01][j] == 3)  // fuel only
{
//   stand_age = per02_age[state][j] *10;

        //SEV = SEV40/(pow((1+INTEREST),(40-stand_age)));

        switch(stand_age)
        {
            case 0:
              //   SEV = SEV_40;
                    SEV = sevValue[4][1];
                break;
            case 1:
```

```
                //  SEV = SEV_30;
                    SEV = sevValue[3][1];
                  break;
            case 2:
                //  SEV = SEV_20;
                    SEV = sevValue[2][1];
                  break;
            case 3:
                //  SEV = SEV_10;
                    SEV = sevValue[1][1];
                  break;
            case 4:
                //  SEV = SEV_00;
                    SEV = sevValue[0][1];
                  break;
        }

        pnw += SEV;
        pnw -= COST*discount_factor;

    }
    else
    {
        switch(stand_age)
        {
```

```
        case 0:
      //     SEV = SEV_40;
             SEV = sevValue[4][1];
             break;
        case 1:
      //     SEV = SEV_30;
             SEV = sevValue[3][1];
             break;
        case 2:
    //       SEV = SEV_20;
             SEV = sevValue[2][1];
             break;
        case 3:
     //      SEV = SEV_10;
             SEV = sevValue[1][1];
             break;
        case 4:
     //      SEV = SEV_00;
             SEV = sevValue[0][1];
             break;
    }

    pnw += SEV;

}
```

```
        }//for(j=0; j<MU; j++)

        current_pnw = pnw;
        if(best_pnw < current_pnw)
        {
            best_pnw = current_pnw;
            best_dec = dec01;
        }

    //  if(dec01 > 1755 && dec01 < 1758)




    }//for(dec01=0; dec01<8: dec01++)

    opt[state][1] = best_dec;
    opt_value[state][1] = best_pnw;

/*
    if(state == 15310*PATTERN)
        printf("--------15310----------\n");

    if(state == 15358*PATTERN)
        printf("--------15358----------\n");
```

```
    if(state == 15342*PATTERN)
        printf("--------15342----------\n");
*/
/*
    if(state == 15342*PATTERN)
        printf("--------15342----------\n");
*/

/*
    if(state >= 15310*PATTERN && state <= 15311*PATTERN )
    {
//      state_temp = state;
        printf("opt decisions = %d", opt[state][1]);
        printf("opt value = %f\n", opt_value[state][1]);
    }

    if(state >= 15358*PATTERN && state <= 15359*PATTERN )
    {
    //  state_temp = state;
        printf("opt decisions = %d", opt[state][1]);
        printf("opt value = %f\n", opt_value[state][1]);
    }
```

```
    if(state >= 15342*PATTERN && state <= 15343*PATTERN )
    {
    //   state_temp = state;
         printf("opt decisions = %d", opt[state][1]);
         printf("opt value = %f\n", opt_value[state][1]);
    }
*/


/*
    if(counter == 128)
    {
         counter = 0;
         printf("------------------\n");
    }

    printf(" opt_decision[%d] = %d ", state, opt[state][1]);
    printf("     opt_value[%d] = %f\n", state, opt_value[state][1]);
*/

    counter++;
}

//The first-second stage optimization:
```

```
for(dec02 = 0; dec02 < DECISION; dec02++) {
     pnw02 = 0;
     current_pnw02_exp = 0.0;

     fuel_counter = 0;

     expect_f = 0.0;

     for(j=0; j<MU; j++)
     {
     // find revenue from the per_1 decision

     ////// May 31 /////////////

          if(dec[dec02][j] == 2 || dec[dec02][j] == 3)
          {
               fuel_counter++;
          }

// fuel constraints!!
     //   if(fuel_counter > 4)
          if(fuel_counter > 7)
               pnw02 -= 100000000000;
```

```
/////end of May 26///////////


if( dec[dec02][j] == 1 )
{
    stand_age02 = init_cond[j][0];

    if(stand_age02 >= 3)
    {
        vol_02 = vol[stand_age02][1];
        pnw02 += vol_02*PRICE - COST_H;
    }
    else
        pnw02 -= 100000000000;

//  vol_02 = vol[stand_age02][1];
//  pnw02 += vol_02*PRICE - COST_H;

}
else if(dec[dec02][j] == 2)
{

    stand_age02 = init_cond[j][0];

    if(stand_age02 >= 3)
```

```
    {
        vol_02 = vol[stand_age02][1];
        pnw02 += vol_02*PRICE - COST_H - COST;
    }
    else
        pnw02 -= 100000000000;

//  vol_02 = vol[stand_age02][1];
//  pnw02 += vol_02*PRICE - COST_H - COST;

    //pnw02 -= 100000000000;

}
else if(dec[dec02][j] == 3)
{
    pnw02 -= COST;
}

else
    pnw02 += 0.0;

}//for(j=0; j<MU; j++)
```

```
//  fprintf(fp_out,"--------------------\n");

//  fprintf(fp_out, "decision at per01: %d  pnw02= %f\n",
               dec02, pnw02);

    fprintf(fp_out, "decision at per01: %d  pnw02= %f
               ", dec02, pnw02);



    // find the expected value
    for(i = 0; i < PATTERN ; i++) // pattern
    {
        prob_p = prob[dec02][i];

    //  printf("prob at dec02: %d    pattern: %d = %f\n",
                   dec02, i, prob_p);

        pattern = i;
        decision = dec02;
        opt_value02 = opt_value[dec02*PATTERN + i][1];

    //  printf("obt_value at the state %d:  %f\n",
               dec02*PATTERN + i, opt_value02);

        expect_f += prob_p*opt_value02;
```

```
    //  printf("expect_f: %f\n", expect_f);
    }// for(i = 0; i < 4; i++) // state

//  fprintf(fp_out, "expect_f: %f\n", expect_f);
    fprintf(fp_out, "  expect_f: %f   ", expect_f);

    current_pnw02_exp = pnw02 + expect_f;

//  fprintf(fp_out,"current_pnw02_exp: %f\n", current_pnw02_exp);
    fprintf(fp_out,"  current_pnw02_exp: %f\n", current_pnw02_exp);

    if(current_pnw02_exp > best_pnw02_exp)
    {
        best_pnw02_exp = current_pnw02_exp;
        best_dec02 = dec02;

    }

 ////////May 25 8:30pm add for testing //////
/*
    if(dec02 == 1550)
    {
        for(i = 0; i < PATTERN ; i++) // pattern
        {
            printf("prob[%d] = %f\n",i, prob[dec02][i]);
```

```
        } // for(i = 0; i < PATTERN ; i++) // pattern

    }
*/
////////////////////////////////////////////////

} // for(dec02 = 0; dec02 < 8; dec02++)



//fp_out = fopen(param[4], "w");
fprintf(fp_out, "best_decision at period 1: %d\n", best_dec02);



for(int h = 0; h < 7; h++){
    fprintf(fp_out, "%d ", dec[best_dec02][h]);
    if(h == 6)
    fprintf(fp_out, "%d\n", dec[best_dec02][h]);
}

fprintf(fp_out, "best_obj_value is %f\n", best_pnw02_exp);

fprintf(fp_out, "best_decision at period 2 \n");

//Printout optimal decision at period 2!!!//////
```

```
/* for(i = 0; i < PATTERN ; i++) // pattern {
     fprintf(fp_out, "opt_decision[%d] = %d\n",i,
                    opt[best_dec02*PATTERN + i][1]);

} // for(i = 0; i < PATTERN ; i++) // pattern

fprintf(fp_out,"prob \n");

for(i = 0; i < PATTERN ; i++) // pattern {
     fprintf(fp_out,"prob[%d] = %f\n",i, prob[best_dec02][i]);

} // for(i = 0; i < PATTERN ; i++) // pattern
*/

fclose(fp_out);

/* printf("if decision is 15310\n"); for(i = 0; i < PATTERN ; i++)
// pattern {
     printf("opt_decision[%d] = %d\n",i, opt[15310*PATTERN + i][1]);

} // for(i = 0; i < PATTERN ; i++) // pattern

printf("prob \n");

for(i = 0; i < PATTERN ; i++) // pattern {
```

```
    printf("prob[%d] = %f\n",i, prob[15310][i]);

} // for(i = 0; i < PATTERN ; i++) // pattern


printf("if decision is 15342\n"); for(i = 0; i < PATTERN ; i++) //
pattern {
    printf("opt_decision[%d] = %d\n",i, opt[15342*PATTERN + i][1]);

} // for(i = 0; i < PATTERN ; i++) // pattern

printf("prob \n");

for(i = 0; i < PATTERN ; i++) // pattern {
    printf("prob[%d] = %f\n",i, prob[15342][i]);

} // for(i = 0; i < PATTERN ; i++) // pattern
*/

/* printf("if decision is 15290\n"); for(i = 0; i < PATTERN ; i++)
// pattern {
    printf("opt_decision[%d] = %d\n",i, opt[15290*PATTERN + i][1]);

} // for(i = 0; i < PATTERN ; i++) // pattern
```

```
printf("prob \n");

for(i = 0; i < PATTERN ; i++) // pattern {
    printf("prob[%d] = %f\n",i, prob[15290][i]);

} // for(i = 0; i < PATTERN ; i++) // pattern
*/

freeimatrix(DECISION, MU, dec); \\
freeimatrix(MU, 2, init_cond);
freeimatrix(2097152, 2,per02_fuel);
freeimatrix(2097152, 2, per02_fuel);
freeimatrix(2097152, 2, opt);
freefmatrix(2097152 , 2, opt_value);
freefmatrix(DECISION, PATTERN, prob);
freefmatrix(5, 2, sevValue);

return 0;

} // main



/*--FUNCTIONS--------------------------------------------------------------*/

int **imatrix( unsigned long rows, unsigned long columns) {
```

```
    unsigned long i;


    /*allocate pointers to rows*/
    int **m = (int**)calloc(rows, sizeof( int*));

    //allocate pointers to vectors
    for(i = 0; i < rows; i++)
    {
        m[i] = (int*)calloc(columns, sizeof( int));

    }

    //memset( m, 0, sizeof(m) );

    return m;
}

float **fmatrix( unsigned long rows, unsigned long columns) {
    unsigned long i;


    /*allocate pointers to rows*/
    float **m = (float**)calloc(rows, sizeof( float*));
```

```
    //allocate pointers to vectors
    for(i = 0; i < rows; i++)
    {
        m[i] = (float*)calloc(columns, sizeof( float));

    }

    //memset (m, 0, sizeof(m));

    return m;
}

double **dmatrix( unsigned long rows, unsigned long columns) {
    unsigned long i;


    /*allocate pointers to rows*/
    double **m = (double**)calloc(rows, sizeof( double*));

    //allocate pointers to vectors
    for(i = 0; i < rows; i++)
    {
        m[i] = (double*)calloc(columns, sizeof( double));

    }
```

```
    //memset (m, 0,sizeof(m));

    return m;
}

void freeimatrix(unsigned long rows, unsigned long columns, int
**imatrix) {

    unsigned long i;

    for(i = 0; i < rows; i++)
        free(imatrix[i]);
    free(imatrix);

}

void freefmatrix(unsigned long rows, unsigned long columns, float
**fmatrix) {

    unsigned long i;

    for(i = 0; i < rows; i++)
        free(fmatrix[i]);
    free(fmatrix);
```

}