AN ABSTRACT OF THE DISSERTATION OF

Young-Hwan Kim for the degree of Doctor of Philosophy in Forest Resources presented on September 22, 2006.

Title: Spatial Patterns of Fuel Management Activities and Their Effects on Wildfire Behavior

Abstract approved:

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Pete Bettinger

Fuel management has been used as an effective local strategy to reduce the undesirable consequences of wildfires. Many efforts toward scheduling of fuel management activities across a broader landscape have been proposed, with the hope of achieving larger landscape-scale management effects. However, scheduling of fuel management treatments across the broader landscape is limited by understandings of how individual management activities aggregate to larger scales and how they affect the behavior of wildfires. Since full coverage of a landscape with fuels management

treatments is unlikely, it is necessary to examine the effects of a spatial pattern of individual management activities at the landscape scale.

In this research, four spatial patterns of fuel management activities – dispersed, clumped, random, and regular – were tested to investigate their potential for reducing the risk of severe wildfire. A new methodology was developed for optimizing fuel management patterns across a landscape based on a heuristic technique and GIS databases. To quantify the cumulative effects of fuel management patterns for disrupting the progress of wildfires, overall flame length, fireline intensity, and fire size were measured for simulated fires, using a fire growth simulation model, FARSITE.

The management scenarios generated from the scheduling model presented a variety of dispersion and treatment sizes, but also evenly distributed the harvest volume through the multi-decade time horizon. The optimized spatial patterns were qualified through visual examination as well as a statistical assessment.

Through this research, I have learned that the efficiency of fuels management activities for reducing severity of wildfire is primarily influenced by treatment size, type, and intensity. Most importantly, treatment types and intensity are the critical factor to disrupt human-caused wildfires. The regular pattern seemed to be the most acceptable for either random ignitions or hypothetical human-caused ignitions. It provided the highest frequency in which simulated fires could contact the treated units, and higher treatment intensity measured by amount of harvested volume from a unit area. To enhance the results of this research, we suggest that one should utilize more feasible

management prescriptions for post-fire fuel conditions, and expand ignition sources to other type of human-caused ignitions or natural-caused ignitions.

Spatial Patterns of Fuel Management Activities and Their Effects on Wildfire Behavior

by

Young-Hwan Kim

A DISSERTATION

submitted to

Oregon State University

in partial fulfillment of

the requirements for the

degree of

Doctor of Philosophy

Presented September 22, 2006

Commencement June 2007

Doctor of Philosophy dissertation of Young-Hwan Kim

presented on September 22, 2006.

APPROVED:

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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.

Young-Hwan Kim, Author

ACKNOWLEDGEMENTS

I was 27 years old when I first came here in the U.S. with my wife. I was given two daughters afterward. There was no doubt that I was responsible to take care of my family, but I most concerned myself. I was extremely proud of myself and strongly believed in my ability. I was really a man of arrogance, but nothing without egoism.

However, everything has changed during the last 7 years in my graduate study. I became one of us. I became one of my communities. I became one of my family members.

Now, I am called, “Dad”, in my family. Jesus, I really love that.

Indeed, I realized

I got an advisor, who always guide me like a shepherd,

I got committee members, who provided much assistance and advice,

I got a supporter who has gave financial aids for my research project,

I got a lot of friends and colleagues, who encouraged me to keep up,

I got parents, who have supported and concerned me,

I got adorable daughters, who always show me a nature of love, and

I got a lovely wife, who present faithful encourage and countless sacrifices.

I appreciate all of you,

The advisor, Dr. Pete Bettinger,

Committee members, Dr. Jack Walstad, Dr. Paul Doescher, Dr. Lisa Madsen, and Dr. Starr McMullen,

The supporter, Dr. Mark A. Finney,

The mentors, Dr. Jo Tynon, Dr. Man-Yong Shin, Dr. Hanho Kim, and Dr. Ki-Jun Yoo,

Friends and Colleagues, David Graetz, Kee-Woong Park, Suil Park, Sung-Won Shin, Eunho Im, Hoonbok Yi, Doo-Hyung Lee, and Sung-Hyun Choi,

Pastor, Gwang-Rae Park,

Parents, Ja-Pyung Kim and Soon-Kyo Seo,

Parents in law, Jae-Chan Heo and Ok-Su Jang,

Daughters, Allie and Amber, and

Wife, Jee-Young.

Special thanks are extended to God who allows me to do my work with these perfect people in the perfect place and time.

"How precious to me are your thoughts, O God! How vast is the sum of them!" (Psalms 139:17)

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CHAPTER 1

GENERAL

INTRODUCTION

1.1 INTRODUCTION

During the last decade, many efforts have been invested in fuel management strategies with the hope of reducing undesirable consequences of wildfires (cost, size, ecological damage, and threat to developed areas). Fuel management in individual management units is expected to modify fire behavior at small scales, but alone may have negligible impact on the overall growth and behavior of larger fires across a landscape.

Fire behavior may be altered by fuel management activities only when they are scaled and arranged with the intent to disrupt the progress of the fire. Thus, a large-scale scheduling process is required to achieve landscape-scale management effects. However, existing efforts toward the scheduling of fuel management activities is limited by a poor understanding of how individual management activities aggregate to larger scales and affect growing fires. Therefore, it is essential to examine the effects of spatial patterning of individual management activities on wildfire behavior at the landscape-scale.

In this research, several spatial patterns of management activities were examined to investigate their effectiveness for reducing the risk of intense fire. This research started from a basic question, how to schedule individual fuel management activities in patterns spatially and temporally across a landscape. Since research to date has not provided enough methodology for scheduling fuel management activities with respect to their spatial patterns, a new methodology based on a heuristic technique, along with the appropriate GIS databases, was developed for arranging management activities

across a landscape. To investigate the effects that fuel management patterns have on altering landscape-fire behaviors, in terms of efficiency and effectiveness, overall flame length and fireline intensity were measured from a fire growth simulation model, FARSITE.

1.2 JUSTIFICATION AND EXPECTED ACCOMPLISHMENTS

To arrange fuel management activities in diverse spatial patterns, scheduling approaches based on a heuristic algorithm, along with GIS data were developed and tested. I present a new methodology for applying spatial patterns of fuel management activities as a management constraint within forest landscape planning. Although fuel management effects have been heavily studied and their effectiveness for reducing the risk of an intense wildfire have been proven, most of the studies were theoretical in nature, due to the difficulty of conducting experimental work at a sufficiently large scale. As an alternative approach, this research applied a fire simulation model to a real landscape, and presented a means to study spatial and temporal relationship of fire management.

1.3 LITERATURE REVIEW

1.3.1 Fuel Management

Observations of wildland fire growth and behavior among age-mosaics of fuel patterns in the forests of the Sierra Nevada (van Wagtendonk 1995, Parsons and van Wagtendonk 1996) and in chaparral (Minnich and Chou 1997) support the idea that spatial fragmentation of fuels can cumulatively change fire size and behavior. A critical factor, however, is the arrangement, size, and number of management activities across landscape. For example, isolated small management units had negligible effect on the growth and progress of large fires in California chaparral in spite of the reduction of fire spread within the units (Dunn 1989).

Dispersing management units and creating fuel breaks have been proposed as spatial strategies in fuel management plans recently developed for the Boundary Waters Canoe Area (BWCA) (USDA Forest Service 2000) and the Sierra Nevada (USDA Forest Service 2001). The fundamental difference between these two strategies is the conception of the role of individual management units. Fuel breaks are intended to reinforce defensible locations and thereby reduce fire sizes by facilitating suppression (Green 1977, Omi 1996, Weatherspoon and Skinner 1996, Agee et al. 2000). Dispersed management treatments rely on the topology of the management units as parts of a pattern to reduce spread rate and intensity (Finney 2001, Finney in review). With respect to protecting a wildland-urban interface, dispersed management treatments slow

the progress of fire towards the interface while fuel breaks provide defensible space for crews immediately adjacent to developed areas.

1.3.2 Spatial Patterns of Fuel Management activities

The effectiveness of fuel management activities has been examined in prior research. Random patterns of fuel management activities (Finney in review) reduced spread rate in a sigmoid fashion, meaning that relatively large proportions of the landscape must be treated to substantially reduce fire sizes. Finney (in review) also found that random fuel management patterns statistically allow large fires to move faster across a landscape than small fires, because they contain larger areas of fast-burning fuel types.

Parallel strips (Fujioka 1985, Martin 1988, Catchpole et al. 1989) are most efficient at reducing fire spread rates (producing a harmonic mean spread rate) with small fractions of the landscape treated. However, this strategy unrealistically requires the fire to move perpendicularly to the strips. Regular patterns of dispersed fuel management activities (Finney 2001) can reduce fire spread rate in a similar fashion to parallel strips, but are more flexible in accommodating other spatial constraints.

1.3.3 Fire Simulation

Many landscape simulation approaches are currently used for spatially modeling fire and subsequent forest development (Keane et al. 1997, Jones and Chew 1999, Mladenoff and He 1999). Some of them have been proposed for modeling effects of

management and for optimizing the scheduling of fuel management. However, none of them accounted for the topological effects of fuel management patterns on landscape-scale fire behavior. These models were not designed to allow optimization of management activities in a topological fashion across time and space at both stand and landscape levels. Linear programming techniques are limited in their ability to achieve this requirement due to the need to know exact management prescriptions before run-time, and the absence of space and time controls on management scheduling in linear programming, as well as its limits on modeling random disturbances. Furthermore, for retaining the spatially variable fire effects at a fine-scale resolution, fine-scale landscape units represented as either grids (a raster type GIS) or small polygons (Finney 1999) are necessary. The SAFED model is one approach that allows one to control these issues in scheduling activities and is well suited to preserving the fine-scale resolution of fire effects (Graetz 2000).

The methodology of SAFED originated with the Sierra Nevada Ecosystem Project (SNEP) where effects of fuel breaks were modeled in the context of wildfire occurrence and forest change (Sessions et al. 1999). SAFED is a spatially explicit simulation/optimization tool that features a forest stand dynamics model, a stand management optimizer for dynamically selecting prescriptions at run time (not-prescheduled), a spatially explicit fire growth model, FARSITE (Finney 1998), and a landscape optimization heuristic. These models allow for scheduling of harvesting activities, simulation of wildfire events, growth and mortality of vegetation, surface and crown fuel development, and specification of stand-level and landscape-level

objectives. SAFED currently, however, does not allow one to optimize the spatial pattern of fuel management activities, and is no longer in development nor supported by the original researchers.

1.4 CONCLUSION

The literature review provides an overview of the current research on the effects of fuel management activities and their effects on wildfire behavior, limitations in the fire simulation research concerning cumulative effects of management activities dispersed across landscape, and the current development of fire growth simulation models. In order to understand how individual management activities aggregate to the landscape scale and affect the behavior of growing fires, it is necessary to quantify the effects of spatial patterns of individual management activities on a real landscape by using a fire simulation model.

1.5 METHODS

1.5.1 Research Design

In this research, 4 spatial patterns for dispersing fuel management activities were examined. Three basic landscape patterns – dispersed pattern, random pattern, and clustered pattern (Forman and Godron, 1986) – and one artificial pattern – regular pattern – were examined (Figure 1.1). These spatial patterns of fuel management

activities were scheduled with a heuristic modeling technique. Great Deluge Algorithm (Dueck, 1993), one of common heuristic algorithms used in natural resource management, was applied for the scheduling of fuel management activities. For each fuel management pattern, the scheduling procedure was repeated 30 times to find the best solution that optimizes the pattern temporally and spatially across landscape. For quantifying the effects of retained solutions more accurately, a control solution with no management activities was also generated.

Overall fire growth or intensity distribution across the landscape under the above solutions was quantified using FARSITE (Finney, 1998) with several random ignition points. The measurements of the control solution were then compared with other solutions to test the following hypothesis:

> Hypothesis 1: Fuel management activities that are scaled and arranged in spatial patterns are effective in altering landscape scale fire behavior.

Also, the measurements of the solutions for each spatial pattern were compared to each other to test Hypothesis 2:

> Hypothesis 2: Cumulative effects of individual fuel management activities on landscape-scale fire behavior vary in direct relation to the spatial pattern in which they lie.

Because the study site was not randomly selected, this research was an observational study and the scope of inference was the study site itself. There was no representation to a wider population. However, the fire simulation was carried out across the whole study site for each spatial pattern, so conclusions were drawn about the difference between the effects of spatial patterns within the study site.

1.5.2 Site Description

The study site is a large watershed, the Grand Ronde River basin (approximately 178,000 hectares) in northeastern Oregon (USA) (Figure 1.2). Most of the area is managed by the U.S. Forest Service (Wallowa-Whitman National Forest), however some private land exists in the middle of the basin.

1.5.3 Data Collection

Geographic information system (GIS) databases representing the forest structure of the study area were downloaded from the website of the Interior Northwest Landscape Analysis System (INLAS) project (http://www.fs.fed.us/pnw /lagrande/inlas/index.htm). The given GIS data are in a shape file format that was generated using ESRI products, ArcView and ArcMap. When scheduling activities across the landscape, centroids of management units were used as a proxy for their locations. Thus, by using ArcView software and its extensions, centroids of management units were generated and their x, y coordinates were available. In addition, scheduling of fuel management activities required attribute data accompanied with GIS

databases that describes the specific vegetation structure of each management unit. Thus, all required attribute data were exported in ASCII format, and then made feasible for the various scheduling procedures described in following chapters.

Data of stand structure and available harvest volume for each management stand are essential in scheduling management activities. Thus, changes in stand condition and harvest volume available from several management activities were simulated over 10 ten-year periods (100 years) using a stand-level optimization model, SLOMO (Graetz and Betternger 2005). The forest structure conditions projected by SLOMO for several management activities were utilized in fuel management planning.

1.5.4 Scheduling Model

Today forest planning is forced to accommodate forest regulations that increasingly place restrictive limits on the size and spatial relationships of harvesting units (Daust and Nelson 1993). As a result of incorporating spatial goals such as clear-cut adjacency restrictions, forest planning problems have become more complex and require extremely larger solution space. Linear or mixed integer programming techniques, two traditional optimization tools, are limited when they are applied to large planning problems incorporating spatial concerns (Lockwood and Moore 1993).

Heuristic techniques become more prevalent for forest planning with complex and non-linear goals that traditional optimization techniques are unable to solve. Although several heuristic algorithms have been developed, and are often applied in modified versions, most of them perform the following common steps:

a) Start with random assignment of a management prescription to each management units.
b) Apply random mutation or variation of prescription on management units.
c) Evaluate feasibility of the revised solution for desired management constraints.
d) Retain the 'best' revision
e) Repeat steps b – d until certain stopping conditions are met as well as possible.

Objective Function

In the scheduling procedure, management objectives and constraints were defined as mathematical functions. The calculated objective function values were used for evaluating the efficiency, and the constraints for evaluating the feasibility of a solution. The critical issue was how to define the objective function and constraints for optimizing the spatial patterns of fuel management activities. In this research, we used a utility function that simultaneously optimized even-flow timber harvest volume and the spatial arrangement of management activities. This is described in more detail in Chapter 2.

1.5.5 Fire Simulation

FARSITE (Finney 1998), a fire growth simulation model, was developed as individual software with a window-based interface. It has been widely used by both federal and state agencies, and applied in several research projects (van Wagtendonk, 1996; Stephens, 1998; Finney, 2001; Finney, 2003; Stratton, 2004). For the fire growth

simulation, several field conditions – both environmental and topographic – are required as input to FARSITE. Weather and fuel conditions are the most important input data for a simulation. To quantify cumulative effects of fuel management patterns on landscape-scale fire behavior, specific ranges of weather and fuel conditions should be defined. Fire behavior under worst-case conditions may not be sensitive to management activities. However, fires under such conditions are rarely controlled by fire suppression, thus fuel management should aim at altering fire behavior under severe weather conditions. A sample weather condition from an extreme fire season in eastern Oregon was used in fire simulation.

Testing Hypotheses

Measurements from fire simulations based on each spatial pattern of management activities were analyzed to test the two hypotheses. Each solution included prescriptions for 10 management periods (100 years), but fire simulation was conducted only for the first management period when the first management activities were completed, due to a limitation of scheduling process (see Chapter 2).

To test hypothesis 1, I developed a control solution with no management activities assigned to the landscape. A fire simulation was then applied to the control solution and compared with the simulations of each spatial pattern of management activities. This comparison could verify the effectiveness of each fuel management pattern in altering landscape-scale fire behavior. Also, the fire simulation outputs of each spatial pattern were compared to each other to test hypothesis 2. This comparison

could provide quantifiable differences between the effects of spatial patterns and provide guidance for scheduling management activities across the landscape with intent of reducing the risk of intense fire.

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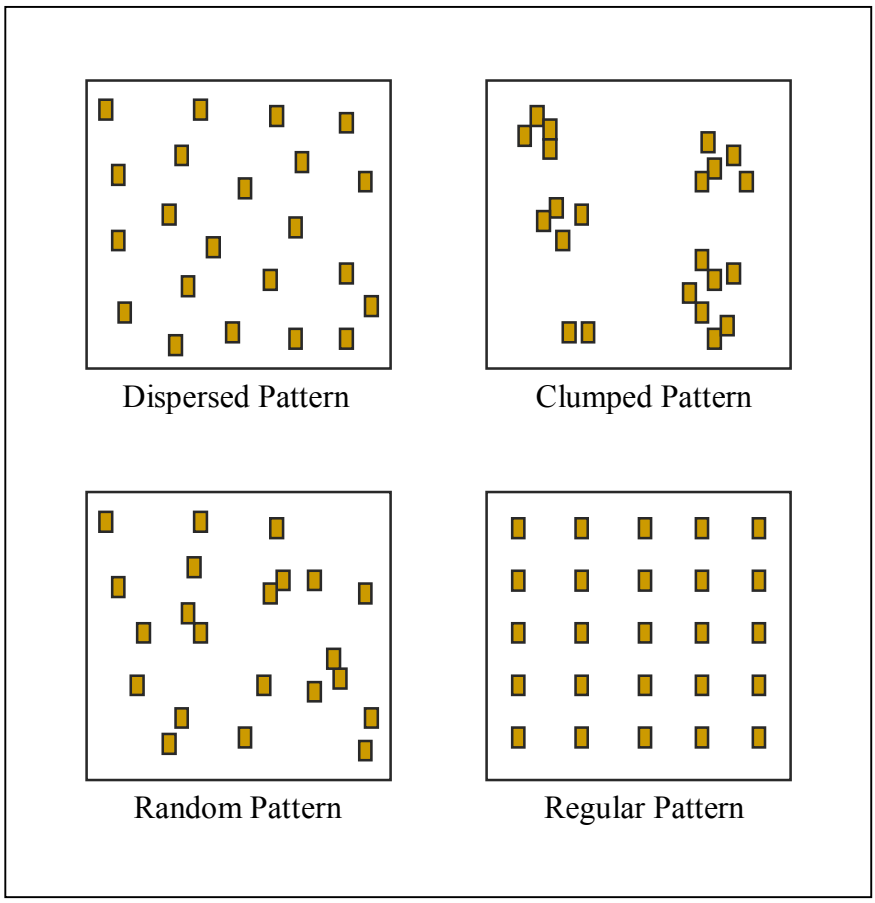

Figure 1.1 – Spatial Patterns of Fuel Management Treatments

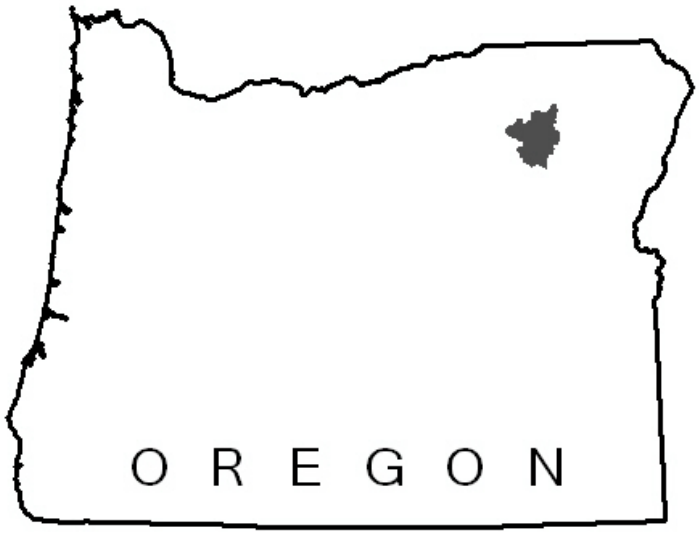

Figure 1.2 – Study site: Upper Grand Ronde river basin in eastern Oregon (USA)

CHAPTER 2

SPATIAL OPTIMIZATION OF FUEL MANAGEMENT

Kim, Young-Hwan

(Submitted to *Ecological Modelling*)

2.1 ABSTRACT

We describe and assess several methods for scheduling forest fuel management treatments to achieve timber harvest and landscape pattern goals across space and time. Four landscape patterns of management activities are modeled (dispersed, clumped, random, and regular). The intent was to examine the effects of spatial and temporal placement of fuel management activities on resulting wildfire behavior. The timber harvest goal is a common one related to the management of public land in the intermountain U.S., to achieve and maintain a high level of even harvest volumes. We described a forest planning scheduling process that provided schedules of activities across both space and time, with the hypotheses that (a) fire effects may be minimized by scheduling activities in a pattern across the landscape, and (b) harvest levels will not be significantly affected by scheduling activities in a pattern across the landscape. Results indicated that while spatial patterns cannot be statistically validated, due to the multi-objective nature of the planning problem, visual examination suggested the patterns are being designed. In addition, fire behavior, as compared to a control simulation with no scheduled activity, was not minimized by scheduling activities in specific spatial patterns. Two reasons for this result emerged: (1) that the prescriptions used, which were designed to promote the development of forest structure within a desired range of stand density, were not appropriate for contributing to the control of wildfire, and (2) increased harvest levels obscure the pattern of activity, making the

impact of the pattern less clear even though harvest levels were not significantly influenced by scheduling them in a pattern across the landscape.

2.2 INTRODUCTION

Western forests in the U.S. have been threatened with high risk of catastrophic wildfires during the last few decades. To reduce a number of undesirable consequences of catastrophic wildfires (i.e., cost of suppression, size of fires, ecological damage, threats to developed areas, etc.), fuel management treatments have been extensively applied to this region. Individual fuel management activities might be expected to affect fire behavior on a very local scale (Helms, 1979; Martin et al., 1989; Agee, 1998), but alone, may have limited influence on the overall behavior of wildfires at large landscape-scale. However, it would be virtually impossible to treat entire forestlands in this region, so management activities need to be scaled and arranged in ways that are surmised to effectively disrupt the progress of wildfires. Therefore, it is important to understand the cumulative effects of individual fuel management treatments and their spatial and temporal pattern of implementation that may affect fire behavior.

Because of the difficulty of conducting experimental work at a large scale, and because of the unpredictability of wildfire, previous research regarding the spatial arrangement of fuel management activities and their effects on wildfire has been mostly theoretical. However, observations of forest fuel patterns in California (van

Wagtendonk, 1995; Parsons and van Wagtendonk, 1996) supported the idea that spatial fragmentation of forests (creating stands of various fuel conditions) can affect wildfire size and behavior. Since isolated attempts in managing forest stands were revealed to have no effect at all on the progress of a fire burning across a large landscape (Dunn, 1989), it seems important to understand how individual fuel management activities aggregate to larger scales, and thus affect the behavior of wildfire, and to understand the appropriate amount of treatments needed to efficiently disturb the growth of wildfires. However, little is known about the cumulative effect of treatments that are spatially and temporally allocated across large areas.

Several basic spatial patterns of management activities have been examined on a smaller scale for their usefulness in controlling wildfire based on the amount of overlap between management activities. For example, the random pattern (Finney, 2003) of fuel management activities places no emphasis on overlap, and thereby reduces spread rate of fires in a sigmoid fashion, inferring that relatively large areas of a landscape must be treated with fuel management activities to substantially reduce fire sizes. Parallel strips of management activities (Fujioka, 1985; Martin, 1988; Catchpole et al., 1989) accommodate complete overlap in one direction. This is one of the most efficient patterns for reducing the spread rates of wildfires with a small amount of treatments necessary. One disadvantage of using parallel strips is that one assumes, unrealistically, that wildfires always move in a direction perpendicular to the strips. Regular patterns of dispersed fuel management activities (Finney, 2001) provide partial overlap, and can reduce wildfire spread rate. These may be more flexible to implement, as well as to

accommodate other spatial management constraints (i.e., adjacency and green-up rules) because the activities are not connected.

Several landscape simulation models have been used for modeling wildfire and forest management activities (Keane et al., 1997; Jones and Chew, 1999; Mladenoff and He, 1999). Some of these models have been proposed for simulating the effects of fuel management activities as well as for optimizing the scheduling of activities with economic objectives. None of the models, however, account for the topological effects of fuel management patterns with respect to landscape-level wildfire behavior. For optimization of fuel management in a topological manner across time and space at the stand level as well as the landscape level, a model is required to recognize spatial relationships, and to accommodate tracking the fine-scale conditions of forest stands. Therefore, the use of integer decision variables and heuristic or simulation models are recommended rather than linear programming or state-transition models (Plant and Vayssières, 2000), given the non-linear nature of the problem.

The overall objective of this study was to understand how spatial patterns of fuel management activities influence wildfire behavior. In this paper, I primarily described and assessed methodologies for arranging fuel management activities in desired patterns across space and time, using a heuristic scheduling process. Also, we examine the effects of optimized spatial patterns of activities on wildfire behavior when applied to a larger watershed in eastern Oregon (USA).

2.3 METHOD

2.3.1 Study Site and Data Preparation

In previously reported preliminary research (Kim and Bettinger, 2005), scheduling methodologies for spatial arrangements of management activities were tested in private lands located within the Upper Grand Ronde River basin in northeastern Oregon (USA). Most of this area is surrounded by U. S. Forest Service land (Wallowa-Whitman National Forest). In this expanded research, the same methodologies were applied to a larger watershed, the entire region of the Upper Grand Ronde River basin (approximately 178,000 hectares, Figure 2.1). Geographic information system (GIS) databases representing the current forest structure of the watershed were downloaded from the website of the Interior Northwest Landscape Analysis System (INLAS) project (http://www.fs.fed.us/pnw/lagrande/inlas/index.htm). When scheduling activities across the landscape, centroids of management units are used as a proxy for their locations. Thus, by using ArcView software and its extensions, centroids of management units were generated and their x, y coordinates were available. In addition, scheduling of fuel management activities required attribute data accompanied with GIS databases that describes the specific vegetation structure of each management unit. Thus, all required attribute data were exported in ASCII format, and then made feasible for the various scheduling procedures described in following chapters.

2.3.2 Scheduling of Spatial Patterns of Fuel Management Activities

Four spatial patterns of fuel management activities were examined in this research, which includes three basic landscape patterns (dispersed pattern, clustered pattern, and random pattern) and an artificial pattern (regular pattern). These spatial patterns of fuel management activities were scheduled with a heuristic modeling technique: the Great Deluge Algorithm (GDA) which was introduced by Dueck (1993) and applied to forest planning problems in Bettinger et al. (2002), and Kim and Bettinger (2005). The GDA has not previously been applied to forestry problems of this size, however.

The amount of fuel management treatment might be important in altering fire behavior. If the treatment amount is too small, there may be little management effect because fires might burn with little contact to treated management units. Therefore, two levels of target volume of timber harvests – high and low – were applied in the scheduling process to examine the variance of effects according to treatment amount. In Bettinger et al. (in press), a maximum even-flow harvest volume (200,716 MBF per decade) was determined using linear programming with simplifying management assumptions (i.e., no spatial constraints were considered and continuous variables were used to represent choices assigned to management units). Since a spatial constraint is considered in our research, the two target even-flow volumes were selected from values less than the theoretical maximum: a high volume target (100,000 MBF) and a low target volume (10,000 MBF).

For the low target volume, scheduling procedures were repeated 30 times for each pattern to find the best solution that spatially optimizes a desired pattern across landscape and achieve the even-flow volume. However, for the high target volume, scheduling procedures were repeated only 10 times due to time constraints. Each repetition started with a random schedule of management activities to make the resulting solutions independent. For quantifying the effects of solutions more accurately, a control solution with no management activities scheduled was also generated.

Dispersed Pattern of Fuel Management Activities

In a dispersed pattern, generally management units are widely spread across landscape with minimum clustering. Here, ideal dispersed patterns are assumed to maximize total distance between management units, and also minimize deviations between actual harvest volume and a harvest volume target. The following objective function was developed to generate a pattern as close to the ideal pattern:

Minimize

$$WH \sum_{k=1}^{P} \left(\left| \left(\sum_{i=1}^{N_k} H_{ik} \right) - T \right| \right) - WD \sum_{k=1}^{P} \left(\sum_{i=1}^{N_k - 1} \sum_{j=i+1}^{N_k} D_{ij} \right) \qquad [1]$$

Where:

WH: Weight corresponding to the even-flow harvest volume

WD: Weight corresponding to the dispersion ($WH + WD = 1$)

H_{ik} : Harvest volume from unit i in time period k ($i = 1, 2, \ldots, N_k$, $k = 1, 2, \ldots, P$)

T : Target volume of timber harvesting

D_{ij} : Distance between centroids of unit i and j ($i = 1, 2, ..., N_k$-1, $j = 2, 3,..., N_k$)

i, j : Index of management units scheduled for harvest

k : A time period

P : Total number of time periods ($P = 10$)

N_k : The set of management units scheduled for harvest in time period k

A scheduling procedure based on the above function seeks a solution that minimizes the difference between actual harvest volume and a harvest volume target, and maximizes the total distance between centroids of management units scheduled for harvest. The basic implementation of GDA seeks a solution with a higher peak (higher objective function value) as water-levels (threshold value) increase, to produce a solution which is expected to have highest peak (maximum objective function value). Since the optimized solution in this research was expected to have the minimum objective function value, the algorithm was modified to seek a solution with a lower bottom (lower objective function value) as water is discharged (Figure 2.2). Three stopping criteria were used in the modified version of GDA: total iterations, non-

improved iterations, and water-level. Parameters associated with these stopping criteria are provided in Table 2.1.

Objective function values might obviously vary when assigning weights for each portion of the function, so nine weight combinations (0.9, 0.8, 0.7, … , and 0.1) were tested to determine the most appropriate weights for both patterning and even flow objective. From these test trials, two weight values (WH = 0.4 and WD = 0.6) were chosen for further processing. The choice of weights was made by evaluating the point where dramatic differences in the objective values occurred (i.e., the threshold where a change in weights caused dramatic declines in the objective function value).

The scheduling process for the high level of target volume consumes much more modeling time than that for the low level of target volume. Although weighting each portion of the objection function provided better solutions in case of the low target volume, tremendous time would be required to test the variety of weight combinations for the high target volume. Therefore, the same weights (WH = 0.4 and WD = 0.6) were used for both the high and low target volumes. Moreover, in order to accelerate the scheduling process for the high target volume, it was inevitable to adjust the value of parameters associated with stopping criteria. The adjusted parameters were also given in the Table 2.1.

Clumped Pattern of Fuel Management Activities

A clumped pattern was assumed to be a pattern in which management units are clustered on landscape. Here, the ideal clumped pattern was assumed to minimize the

total distance between management units and minimize the deviation between actual harvest volume and a harvest volume target. The clumped pattern was expected to minimize total distance between management units, while the dispersed pattern is expected to maximize it. Thus, equation 1 was modified to accept this distinction by adding the two portions of the objective function as follows:

Minimize

$$WH \sum_{k=1}^{P} \left(\left| \left(\sum_{i=1}^{N_k} H_{ik} \right) - T \right| \right) + WD \sum_{k=1}^{P} \left(\sum_{i=1}^{N_k - 1} \sum_{j=i+1}^{N_k} D_{ij} \right) \qquad [2]$$

The scheduling procedure now seeks a solution that minimizes the difference between actual harvest volume and harvest volume target and also minimizes the total distance between centroids of management units scheduled for harvest as well. The optimization of clumped pattern was conducted using the same scheduling process with that of dispersed pattern. However, some of the parameters related to the stopping criteria – initial water level and minimum water level – were altered based on trial runs of the scheduling model (Table 2.1). Nine weight combinations were also tested for the scheduling process of the low target volume, and the most appropriate weight values (WH = 0.5 and WD = 0.5) were chosen and used for both the high and low volume targets.

Random Pattern of Fuel Management Activities

A random pattern is a pattern in which management units are randomly allocated across landscape. Within the GDA scheduling process, management units are randomly chosen and random prescriptions are assigned to them, so solutions generated within this process were assumed to have random pattern across the landscape (although the pattern may be influenced by the distribution of vegetation types in the study area). Therefore, the scheduling of a random pattern has no concern with the dispersion of management units, and the only criterion for evaluating the acceptability of a solution is the deviation between actual harvest volume and the harvest volume target through the management periods. Thus, the latter portion of equation 1, which corresponds to the dispersion of management units, is not necessary in the objective function:

Minimize

$$\sum_{k=1}^{P}\left(\left|\left(\sum_{i=1}^{N_k} H_{ik}\right)-T\right|\right) \qquad [3]$$

A few of the GDA parameters have been adjusted based on the trial runs of the scheduling model (Table 2.1).

Regular Pattern of Fuel Management Activities

In general, a regular pattern would be defined as the optimum dispersed pattern, however, it would rarely be found in a natural landscape. In this research, a regular

pattern was assumed to be an artificial pattern in which management units are systematically allocated across landscape with a constant spatial interval. Ideally, management units scheduled for treatment in the regular pattern were expected to have same distance to four neighbor units (northern, southern, eastern, & western). The "interval", therefore, could be defined as a desired distance between centroids of management units that produces an ideal regular pattern. To enable one to generate such pattern, a different approach was developed and utilized for dispersing management units. It is based on the following process:

- Select one initial unit
- Acquire the x, y coordinate of centroid of the unit
- Generate "systematic points" by adding or subtracting a given interval to x, y coordinate of the centroid (Figure 2.3)
- Calculate distance between systematic points and centroids of all units
- Find the nearest centroid for each systematic point
- Check whether each systematic point is located within the boundary of the study site
- Exclude systematic points located outside of the study site
- Save the nearest unit of each systematic point
- Generate a solution by assigning a feasible prescription to the saved units
- Calculate the objective function value and evaluate the solution

One of the issues related to the above idea was how to exclude systematic points located outside of the study site. In order to automate this procedure and to inspect whether a systematic point is out of study site, we needed to test whether a vector connecting a systematic point and its nearest unit centroid was intersected by any boundary vector surrounding the study site. If a systematic point was located outside of the boundary, the vector connecting the systematic point and its nearest unit centroid should be intersected by at least one boundary vector (Figure 2.4). To inspect whether two vectors intersect, a two-step process introduced by Loudon (1999) was used in the scheduling model: a quick rejection test and a straddle test. If both tests succeed, two vectors intersect and thereby, the systematic point was out of the study site.

The quick rejection test is initiated by constructing a rectangle called bounding box that surrounds each vector. A vector between a systematic point and its nearest unit centroid has two end nodes, $n_1 = (x_1, y_1)$ and $n_2 = (x_2, y_2)$. The bounding box of the vector is a rectangle with lower left point $(\min(x_1, x_2), \min(y_1, y_2))$ and upper right point $(\max(x_1, x_2), \max(y_1, y_2))$. Also, a boundary vector has two end nodes, $n_3 = (x_3, y_3)$ and $n_4 = (x_4, y_4)$, and a bounding box with lower left point $(\min(x_3, x_4), \min(y_3, y_4))$ and upper right point $(\max(x_3, x_4), \max(y_3, y_4))$. If bounding boxes of the two vectors intersect, all of the following tests must be true (Figure 2.5):

$$\max(x_1, x_2) \geq \min(x_3, x_4) \qquad \max(x_3, x_4) \geq \min(x_1, x_2)$$

$$\max(y_1, y_2) \geq \min(y_3, y_4) \qquad \max(y_3, y_4) \geq \min(y_1, y_2)$$

A straddle test follows only when the quick rejection test succeeds. To examine whether a vector straddles another, the orientation of n_3 relative to n_2 is compared with that of n_4 relative to n_2. Orientation of n_3 and n_4 convey whether the nodes are clockwise or counterclockwise from n_2 with respect to n_1. The orientation of n_3 and n_4 are determined by following equations:

$$z_1 = (x_3 - x_1)(y_2 - y_1) - (x_2 - x_1)(y_3 - y_1)$$

$$z_2 = (x_4 - x_1)(y_2 - y_1) - (x_2 - x_1)(y_4 - y_1)$$

If the sign of z_1 and z_2 are different, or either one is 0, the vectors straddle each other, and the two vectors intersect. Figure 2.5 describes results of the quick rejection test and the straddle test based on four different cases.

When developing a regular pattern, management units, unlikely to other patterns, are chosen prior to assigning prescriptions to the units. A feasible set of prescriptions for selected management units was assigned to them. As the result, the scheduling process just generated and evaluated the limited number of solutions. In the preliminary research (Kim and Bettinger, 2005), the Tabu Search (TS), a heuristic technique introduced by Glover (1989, 1990), was applied in the scheduling of regular pattern since it was expected to be more efficient than GDA in terms of scheduling time. However, TS was not much more time-efficient, although it produced a similarly efficient result (according to the objective function value). Moreover, using two different heuristic approaches would be achieved by quite an amount of additional

program coding. In this research, the GDA was used as a primary algorithm for all intended patterns, and thereby the scheduling process of a regular pattern was modified (Figure 2.6) from those of previous three patterns.

As described above, management units would be chosen before prescriptions are assigned to them. Thus, assigning a prescription to management units has no influence on the dispersion of management units. This means that dispersion of management units is not an essential element in the objective function any longer. In addition, according to the given prescriptions, a unit scheduled for harvesting in the first time period might be scheduled to be harvested again in one of the following time periods. This means that a set of prescriptions assigned to management units for one time period could affect scheduling of other units in the following time period. By this reasoning, a solution that guarantees a nearly perfect regular pattern in across time periods is rarely obtained. Therefore, the scheduling process seeks a solution that optimizes the harvest from selected management units in the first time period. Upon these matters, the objective function was modified as below:

Minimize

$$\left| \left(\sum_{i=1}^{N} H_{i1} \right) - T \right| \qquad [4]$$

Since a limited amount of information was available to specify the most efficient spatial interval between management units for reducing the fire damage, several

intervals were tested. From the test trials, it was found that the amount of harvest volume is highly associated with the interval. Since the interval might affect not only the dispersion itself, but even-flow harvest as well, a set of various intervals (1.0, 1.5, 2.0, 2.5, 3.0, 3.5, 4.0, 4.5, and 5.0 kilometer) were tested for choosing the most appropriate interval to achieve even-flow harvest of two target volumes, and 4.5 kilometers was selected as the most appropriate interval for the low target volume, and 1.5 kilometers was selected for the high target volume.

2.3.3 Point Pattern Analysis: Nearest Neighbor Distance

In the preliminary research (Kim and Bettinger, 2005), the scheduling model was adequate for optimizing the spatial pattern of management activities and achieving even-flow harvest of target volume. The scheduled patterns across the landscape were evaluated as adequate from visual assessment. However, since there is no statistical test, we were suspicious whether management activities have been scheduled with the desired patterns. To provide confidence to the model, a statistical test was used to assess the scheduled patterns. Therefore, the nearest neighbor distance analysis, which is one of a set of point pattern analysis techniques (Boots and Getis, 1988; Cressie, 1993) was applied to assess the patterns in this research. Within the analysis, the mean of nearest neighbor distance observed from scheduled management activities were compared to the following statistic, the expected mean of nearest neighbor distance for a pattern with complete randomness:

$$d_{\exp} = 0.5\sqrt{\frac{A}{N}} \qquad [5]$$

Where:

$d_{\exp}$: Expected mean distance of nearest neighbor for complete random pattern

A : Area

N : Number of scheduled management units

The hypothesis of this analysis is that a pattern would be random if the observed mean of nearest neighbor distance was not significantly distinct from the expected mean of complete randomness. If the observed mean was significantly less than the expected mean, the pattern would be considered clustered; if it was significantly larger, the pattern would be considered dispersed. The significance of difference between observed and expected mean was tested by using a z-statistic at the 95% confidence level:

$$z = \left[\frac{\hat{d}_{obs} - d_{\exp}}{\sqrt{\mathrm{var}(\hat{d})}} \right] \qquad [6]$$

Where:

$\hat{d}_{obs}$: Observed mean distance of nearest neighbor

$\mathrm{var}(\hat{d})$: Variance $\left(= 0.0683 \times A/N^2 \right)$

2.3.4 Fire Growth Simulation

To quantify changes in fire behavior resulting from fuel management activities and their dispersion, a fire growth simulation model, FARSITE (Finney, 1998), was primarily used. FARSITE is widely used by several federal governments and state land management agencies to simulate the spread of wildfires. FARSITE requires spatial information on topography and fuels along with weather files as inputs, and such inputs should have a grid file format. Thus, input files are prepared using GIS software. To automate the data preparation, the scheduling model, originally developed in the preliminary research, was re-coded and combined with the original code of FARSITE. As the result, generating inputs associated with running FARSITE were seamless within the upgraded version of scheduling model.

FARSITE supports several kinds of outputs describing a simulated fire and its behavior, including: fireline intensity, rate of spread, and flame length. In our analysis, average flame lengths and fireline intensity were primarily used for comparison of treatment effects. To compare the treatment effects according to the patterns, fires with 15 different ignition points were simulated after scheduling activities using each of the four patterns, and the resulted average flame length and average fireline intensity were recorded. The 15 ignition points were selected randomly and applied to every simulation of the four patterns.

2.4 RESULTS AND DISCUSSION

2.4.1 Spatial Pattern of Fuel Management Activities

Management units that were scheduled for treatments in the first time period (decade) and contained in the best solution of each pattern were depicted as Figure 2.7 and 2.8. According to the figures, the distinction between the spatial patterns can be visually verified when the low target volume applied (Figure 2.7), while distinction between patterns is more vague when using the high target volume (Figure 2.8). Because the private land in the center of the study site consisted of a large meadow, management units in the private land were rarely selected for treatment. The lack of treatments within the private land is one reason for the degradation of the spatial pattern, when the high volume target is used.

Point pattern analysis based on nearest neighbor distance revealed a limitation of the scheduling model for patterning treatments. According to calculated statistics from the point pattern analysis (Table 2.2), the regular pattern was validated for both the low and high target volume. When using the low volume target, the random pattern was also validated. However, when using the high volume target, we could not validate the random pattern because of the large number of treatment units. For the clumped pattern, we expected to see a lower observed distance between management units than the expected distance of complete randomness. We found this with the high volume target, thus we assume validation there. However, while the observed distance was lower when using low volume target, the difference between the observed and expected was not

significantly different, thus we can not validate the pattern. The dispersed pattern showed smaller observed distance between management units than the expected distance for both the low and high target volume, contrary to our hypothesis. Besides, when using the high volume target, the observed distance was significantly lower than the expected distance, thus the pattern was considered clumped. We attribute this to the lack of treatment on the private land (mainly meadows) and the availability of treatment opportunities, which is a function of the initial forest structure across the landscape. Although this tendency enabled a dispersed pattern to consist of a large number of management units, the increase of management units could not provide any statistical evidence for validating the dispersed pattern when using the nearest neighbor distance.

2.4.2 Even Flow of Harvest Volume

As shown in the Table 2.3, the best solutions from the four spatial patterns simulated an acceptable even-flow harvest level. Harvest volumes of each spatial pattern are quite close to each target volume across the entire time horizon. However, the best solution for the dispersed pattern had much more variability of harvest volume, as compared to other patterns. The shortage of harvest volume in the second period was due to the prescriptions available to the scheduling procedure, the initial condition of the forest structure and the scheduling procedure itself. There were a limited number of feasible prescriptions to draw from when scheduling management activities in the second period. In optimizing the dispersed pattern, the scheduling model tended to

increase the number of management units entered in the first time period, and thereby management units with less stand volume are available in subsequent time periods.

2.4.3 Fire Simulation

The results of fire simulation were summarized in the Table 2.4. Most of spatial patterns reduced the fire sizes, but did not support sufficient evidence of treatment effect on fire behavior, as indicated by the severity of fires (i.e., flame length and fireline intensity). With the exception of the regular pattern applied to the low target volume, none of the patterns were able to reduce flame length or fireline intensity. Of course, severity of fire behavior was reduced within management units of treatments, but the overall severity of wildfires burning across a large landscape was not much affected by the treatments.

There are several potential reasons that might have caused the lack of treatment effect on fire behavior. One could find a reason in the prescriptions of management activities. The prescriptions utilized in the scheduling procedure were aimed at controlling the stand density through mechanical thinning, but no consideration was given to managing ladder, crown, or surface fuels. These prescriptions might contribute to reduce ladder fuels or crown fuels, but would increase surface fuels. Therefore, additional prescriptions, in which surface fuels are effectively controlled, would be worth assessing.

For investigating the influence of the amount of treatments on fire behavior, two levels of volume targets (10,000 MBF and 100,000 MBF) were utilized in optimizing

even-flow harvest. The solutions optimized for the high volume target included much more management units (Table 2.2) and almost five times the area (Table 2.5), as compared to those optimized for the low volume target. As described in the Table 2.5, treatments (even in the case of high volume target) occupied a small portion (< 7%) of the entire study region. This amount of treatments might not be enough to allow the spatial configurations of activities to disrupt the progress of wildfire. Further, if more efficient prescriptions of fuel treatment were applied, the result of fire simulation could be confounded. Therefore, future work will involve increasing the amount of treatment activity as well as explore other types of management prescriptions.

2.5 CONCLUSIONS

The scheduling model developed in this research provided approaches in which management activities were scheduled in spatial patterns across a large landscape. The solutions optimized through the scheduling process present a variety of dispersion and treatment sizes, but also evenly distributed harvest volume. The scheduling model produced some meaningful results and provided an application of spatial modeling concepts to fuel management activities. However, there were several limitations found as well. First of all, we found through statistical analysis that the scheduling model attempts to allocate management activities in desired patterns but due to the nature of the problem (multi-objective with volume goals) the patterns are not necessarily

statistically achieved. This is mainly due to the number of activities needed to achieve the even-flow harvest target. However, visual examinations suggest that the patterns are being represented fairly well, even though not statistically validated.

The prescriptions used in this research were aimed at controlling the stand density by utilizing mechanical thinning. These were developed in conjunction with a larger landscape planning project and contained operational constraints. According to the fire simulation results, significant differences in fire behavior will rarely be achieved when using these prescriptions, if there is no specific control of ladder, crown, or surface fuels. Increasing the amount of treatments up to 7% of the entire study area each decade was not effective in altering fire behavior either. Therefore, it would seem important to adopt additional prescriptions in the scheduling process, those which have the intent of controlling the critical fuels. However, it is not clear how much treatment is enough to disrupt the progress of wildfire. In further studies, more attention to these remained issues will be paid.

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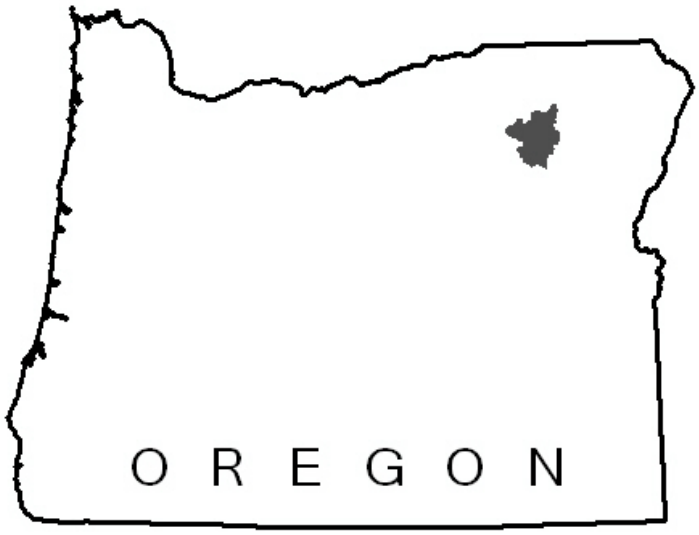

Figure 2.1 – Study site: Upper Grand Ronde river basin in eastern Oregon (USA)

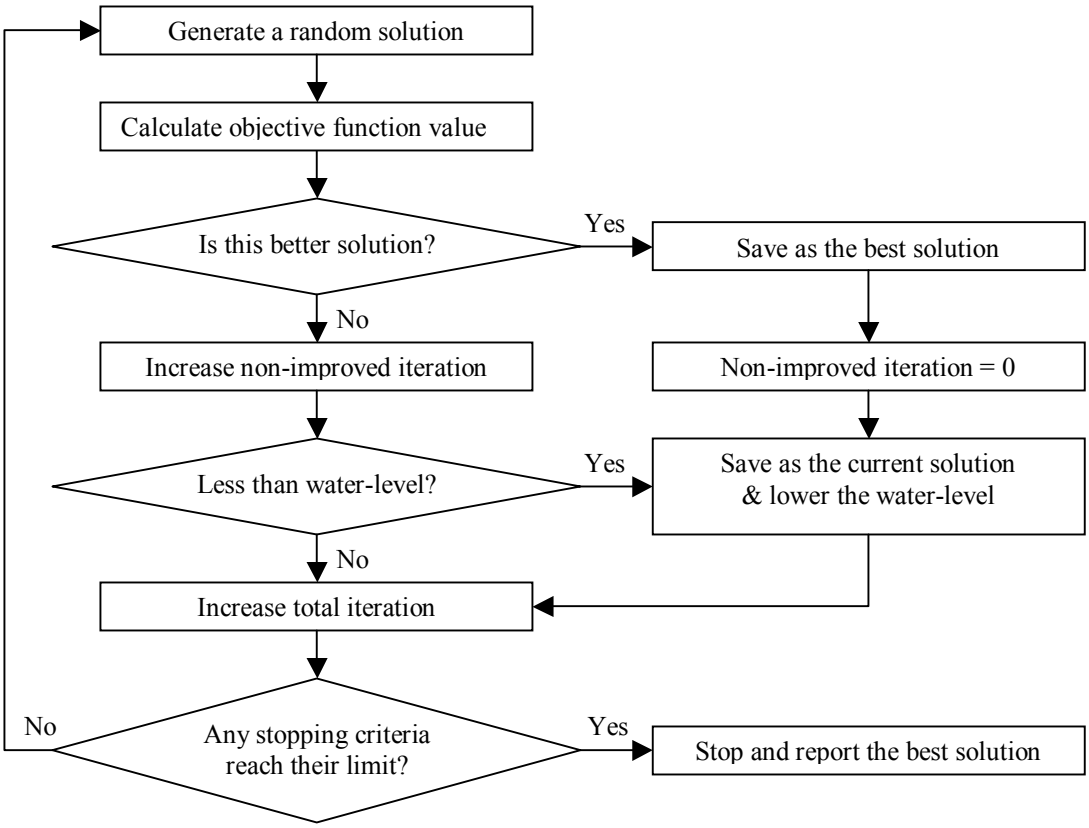

Figure 2.2 – Flowchart of GDA scheduling processes for dispersed, clumped, and random landscape pattern

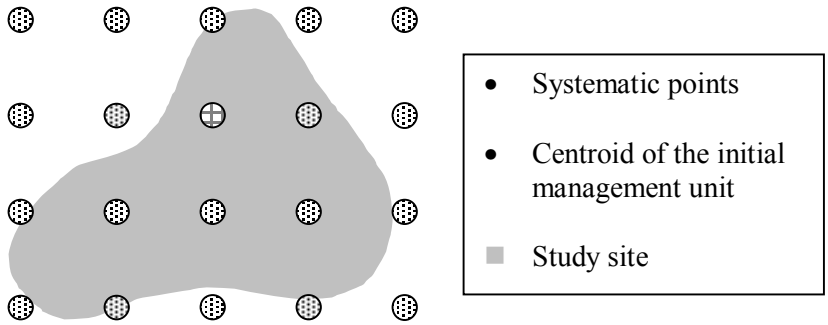

Figure 2.3 – Systematic points generated to facilitate modeling the regular pattern

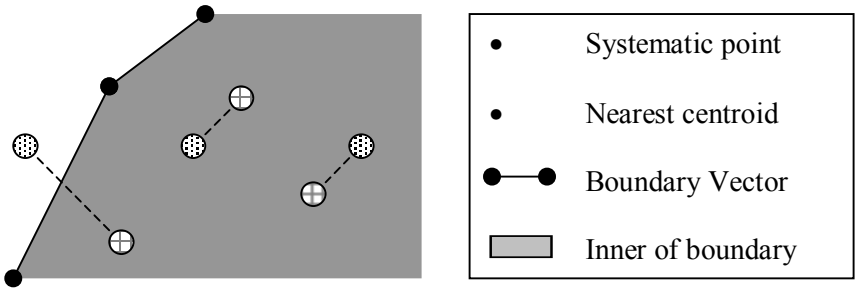

Figure 2.4 – Vectors between each systematic point and the centroid of the nearest neighbor

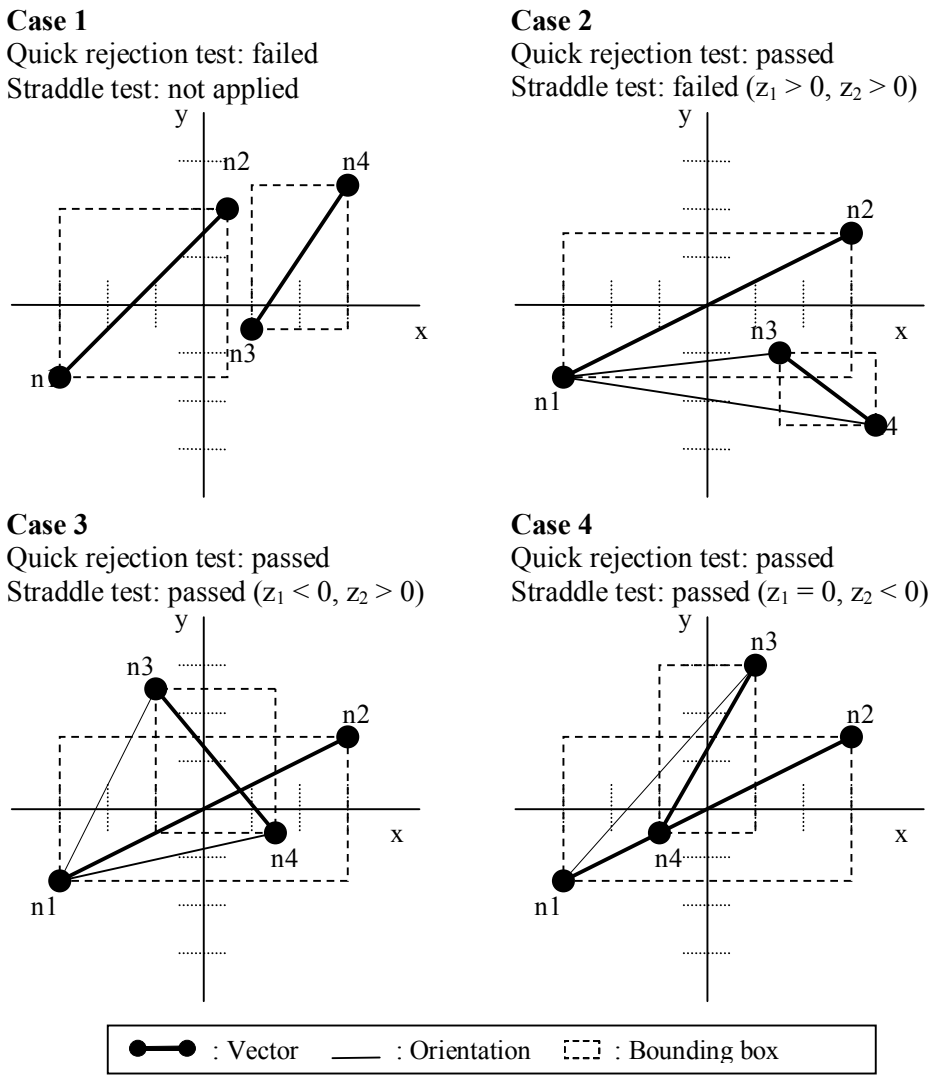

Figure 2.5 – Examples of the quick rejection test and the straddle test for use in the generation of the regular landscape pattern

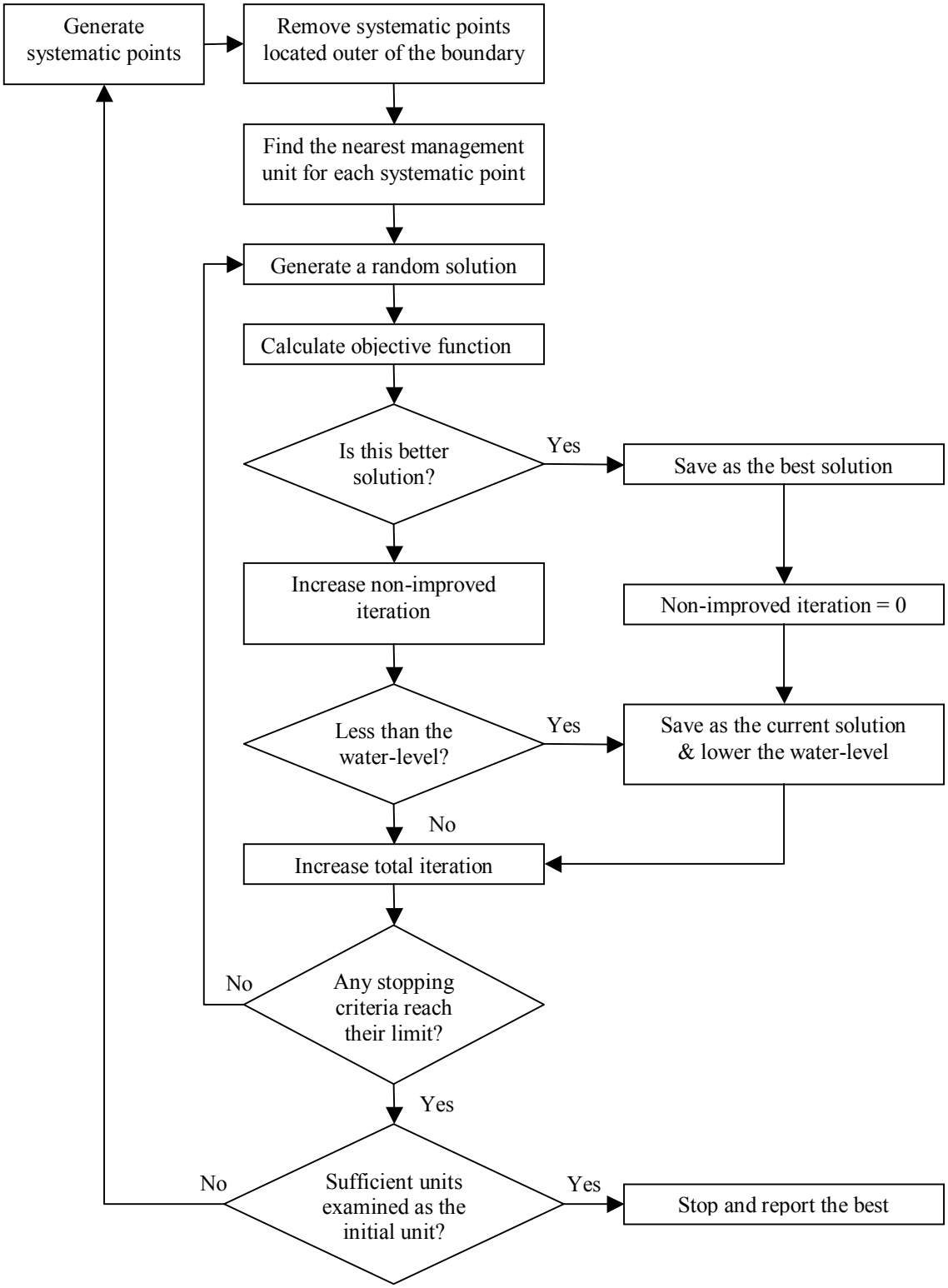

Figure 2.6 – Flowchart of scheduling process for the regular pattern

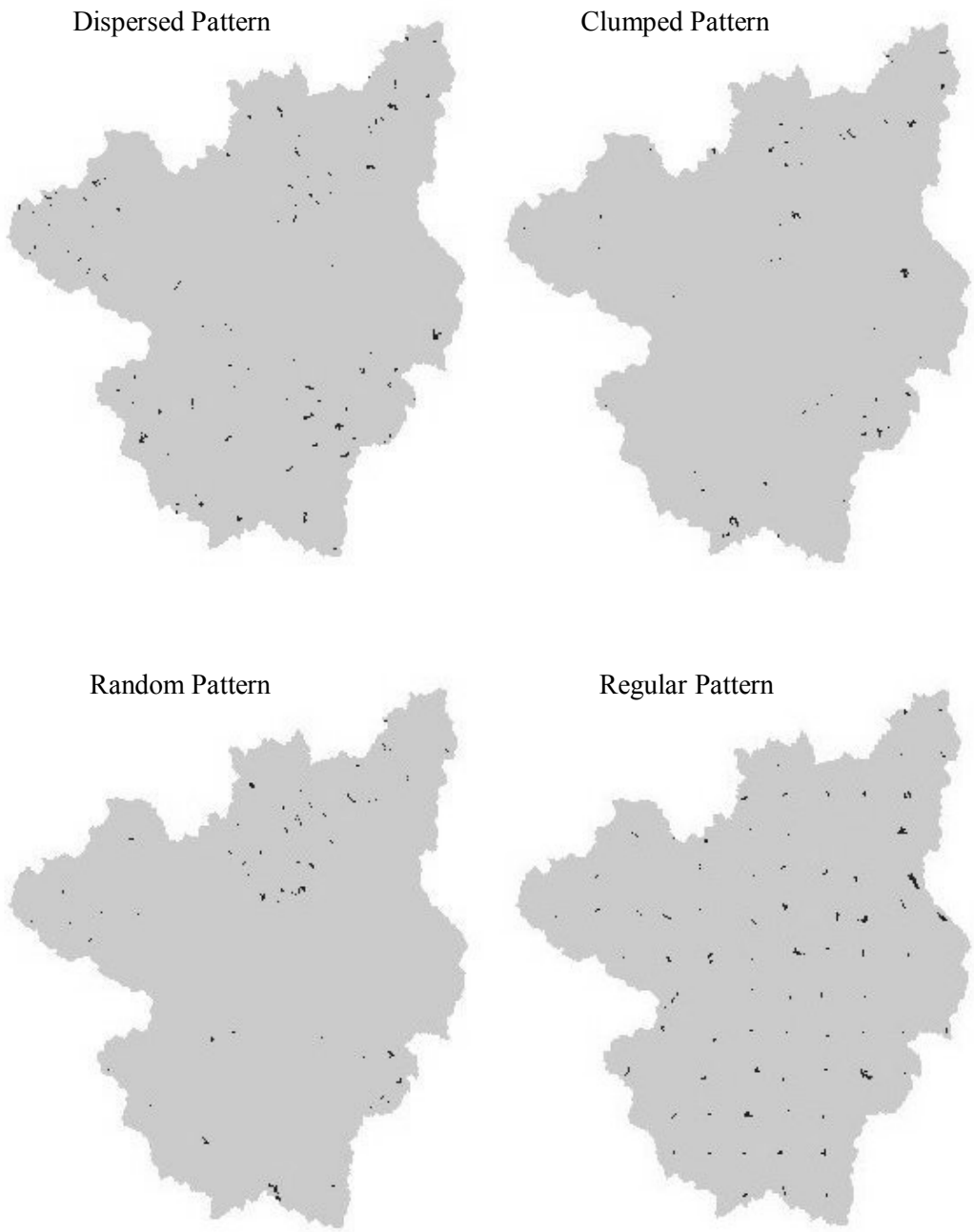

Figure 2.7 – Spatial patterns of management units generated for the low target volume.

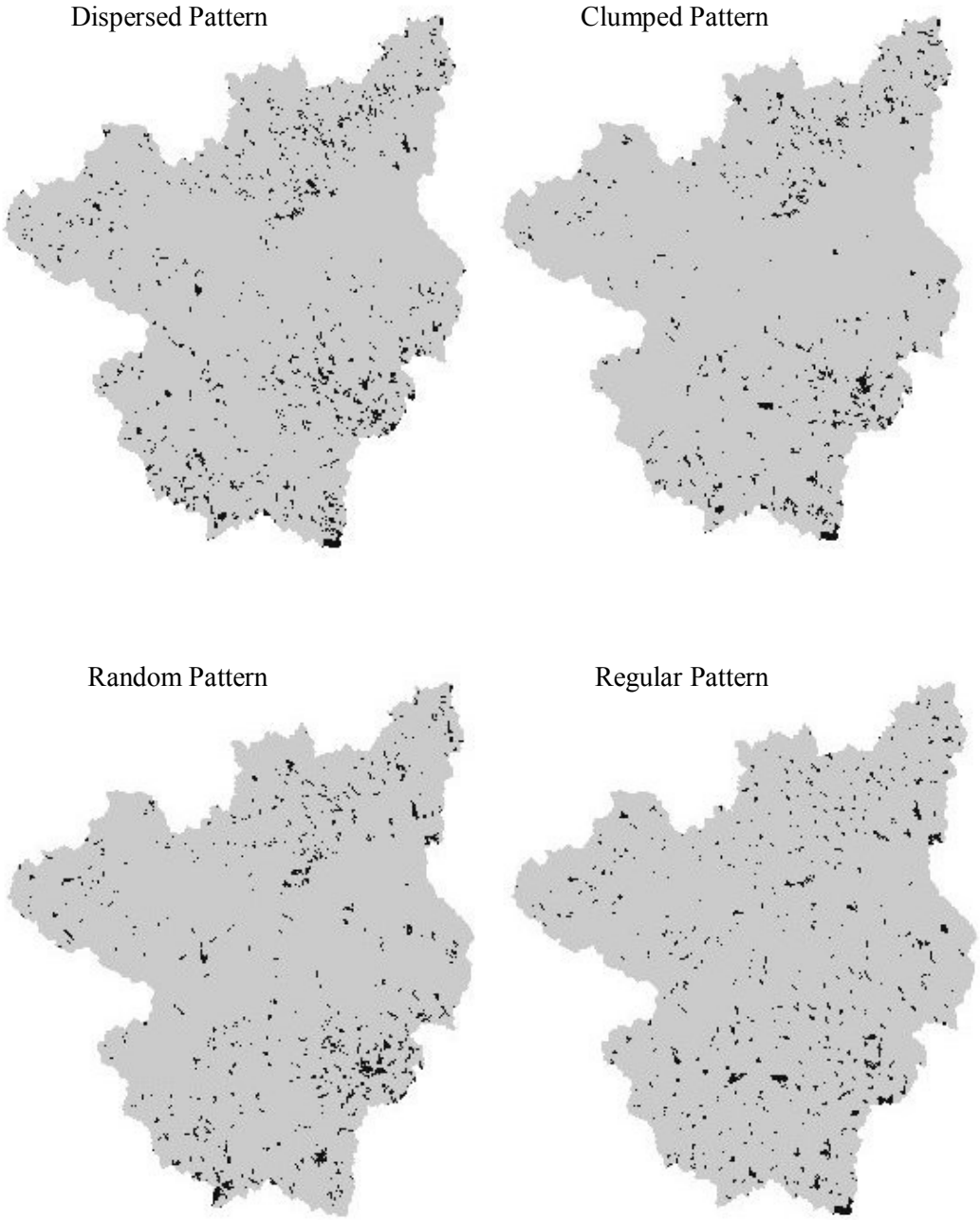

Figure 2.8 – Spatial patterns of management units generated for the high target volume

Table 2.1 – Parameters associated with each scheduling process

Parameters	Dispersed Pattern	Clumped Pattern	Random Pattern	Regular Pattern
Low Target Volume				
Total iterations	200,000	200,000	200,000	100,000
Non-improved iterations	100,000	100,000	100,000	50,000
Initial water-level	5,000,000	10,000,000	5,000,000	5,000,000
Discharging speed	0.01	0.01	0.01	0.01
Minimum water-level	-50,000	0	0	0
High Target Volume				
Total Iterations	150,000	150,000	150,000	150,000
Non-improved Iterations	80,000	80,000	80,000	80,000
Initial water-level	5,000,000	5,000,000	5,000,000	5,000,000
Discharging speed	0.001	0.001	0.001	0.001
Minimum water-level	-100,000	0	0	0

Table 2.2 – Results of point pattern analysis for scheduled patterns of management activities in the first time period

Test Statistics	Dispersed Pattern	Clumped Pattern	Random Pattern	Regular Pattern
Low Target Volume				
# of Units of Treatment	218	56	81	88
Observed Mean (m) [a]	1,417.75	2,641.98	2,552.81	3,803.56
Expected Mean (m) [a] of the randomness	1,430.04	2,821.52	2,346.04	2,250.80
z-statistic	-0.2428	-0.9110	1.5176	12.3815
Validation	Invalid (Random)	Invalid (Random)	Valid	Valid
High Target Volume				
# of Units	967	456	614	476
Observed Mean (m) [a]	602.94	871.05	753.31	1,150.15
Expected Mean (m) [a] of the randomness	678.99	988.77	852.11	967.77
z-statistic	-6.6639	-4.8641	-5.4965	7.8661
Validation	Invalid (Clumped)	Valid	Invalid (Clumped)	Valid

[a] Distance between centroids of management units

Table 2.3 – Harvest volume (MBF) of the best solution for each spatial pattern

Management Period	Dispersed Pattern	Clumped Pattern	Random Pattern	Regular Pattern
Low Target Volume				
Period 1	10,216	10,001	10,000	10,000
Period 2	10,069	10,000	10,000	-
Period 3	9,989	9,999	10,000	-
Period 4	10,257	10,000	10,000	-
Period 5	10,157	10,000	10,000	-
Period 6	10,136	10,000	10,000	-
Period 7	10,273	10,000	10,000	-
Period 8	9,921	10,002	10,001	-
Period 9	10,181	10,000	10,000	-
Period 10	10,080	10,001	10,000	-
High Target Volume				
Period 1	103,286	100,001	100,000	100,000
Period 2	86,484	100,000	100,000	-
Period 3	95,818	100,000	100,000	-
Period 4	101,473	100,000	100,000	-
Period 5	105,317	100,000	100,000	-
Period 6	105,187	100,000	100,000	-
Period 7	113,582	100,000	100,000	-
Period 8	103,039	100,001	100,000	-
Period 9	107,502	100,000	100,000	-
Period 10	95,953	99,998	100,000	-

Table 2.4 – Fire simulation results: fifteen fires applied to each solution

Fire Behavior	Control	Dispersed Pattern	Clumped Pattern	Random Pattern	Regular Pattern
Low Target Volume					
Flame Length (m)	1.02	1.02	1.02	1.02	1.01
Change from control	-	(0)	(0)	(0)	(-0.01)
Fireline Intensity (Btu/ft/s)	427.77	429.53	427.89	428.48	419.66
Change from control	-	(+1.77)	(+0.12)	(+0.71)	(-8.10)
Fire Size (ha)	19,328	19,312	19,328	19,306	20,930
Change from control	-	(-16)	(0)	(-22)	(+1,602)
High Target Volume					
Flame Length (m)	1.02	1.03	1.02	1.02	1.03
Change from control	-	(+0.01)	(0)	(0)	(+0.01)
Fireline Intensity (Btu/ft/s)	427.77	435.81	430.04	434.14	434.82
Change from control	-	(+8.04)	(+2.27)	(+6.37)	(+7.05)
Fire Size (ha)	19,328	18,871	19,141	19,128	18,799
Change from control	-	(-457)	(-187)	(-200)	(-529)

Table 2.5 – Treatment area (ha) of the best solution for each spatial pattern

Management Period	Dispersed Pattern	Clumped Pattern	Random Pattern	Regular Pattern
Low Target Volume				
Period 1	1,432 (0.8%)	548 (0.3%)	847 (0.5%)	1,156 (0.6%)
Period 2	1,732 (1.0%)	894 (0.5%)	993 (0.6%)	
Period 3	1,785 (1.0%)	983 (0.6%)	994 (0.6%)	
Period 4	1,694 (0.9%)	785 (0.4%)	925 (0.5%)	
Period 5	1,860 (1.0%)	990 (0.6%)	1,082 (0.6%)	
Period 6	1,730 (1.0%)	792 (0.4%)	1,044 (0.6%)	
Period 7	1,577 (0.9%)	664 (0.4%)	687 (0.4%)	
Period 8	1,644 (0.9%)	666 (0.4%)	879 (0.5%)	
Period 9	1,638 (0.9%)	667 (0.4%)	764 (0.4%)	
Period 10	1,682 (0.9%)	616 (0.3%)	926 (0.5%)	
Average	1,677 (0.9%)	760 (0.4%)	914 (0.5%)	1,156 (0.6%)
High Target Volume				
Period 1	7,170 (4.0%)	5,182 (2.9%)	6,110 (3.4%)	5,543 (3.1%)
Period 2	8,502 (4.8%)	8,567 (4.8%)	9,634 (5.4%)	
Period 3	9,584 (5.4%)	8,128 (4.6%)	9,186 (5.2%)	
Period 4	9,874 (5.5%)	7,845 (4.4%)	8,732 (4.9%)	
Period 5	11,527 (6.5%)	9,073 (5.1%)	9,542 (5.4%)	
Period 6	10,431 (5.8%)	6,993 (3.9%)	8,419 (4.7%)	
Period 7	10,050 (5.6%)	7,190 (4.0%)	8,230 (4.6%)	
Period 8	9,813 (5.5%)	7,227 (4.1%)	8,591 (4.8%)	
Period 9	9,804 (5.5%)	7,502 (4.2%)	8,169 (4.6%)	
Period 10	9,062 (5.1%)	6,629 (3.7%)	7,806 (4.4%)	
Average	9,582 (5.4%)	7,434 (4.2%)	8,442 (4.7%)	5,543 (3.1%)

CHAPTER 3

CUMULATIVE EFFECTS OF SPATIALLY OPTIMIZED FUEL MANAGEMENT ACTIVITIES

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(Submitted to *Canadian Journal of Forest Research*)

3.1 ABSTRACT

To improve the efficiency and management effectiveness of forest fuel management treatments, it may be necessary to scale and arrange the activities across a large area to affect the overall progress of large fires. This research described the enhancement of a forest planning scheduling model that optimizes spatial patterns of fuel treatments to quantify the effects of treatments on fire behavior and its severity. Four management prescriptions of 'thinning' and 'thinning followed by prescribed burning' activities were generated for forested stands in a large watershed in northeastern Oregon (USA). A heuristic scheduling model was designed to optimize even harvest levels, and four landscape patterns (dispersed, clumped, random, and regular pattern) of activities. Then, fire simulation was conducted using a fire growth simulation model, FARSITE. Results of the fire simulations were examined to test two hypotheses: 1) fire severity may be minimized by scheduling treatment activities in a pattern, and 2) effectiveness of scheduled treatment activities will be influenced by the amount of treatment activities. The fire simulation results indicated that fire severity could be reduced by scheduled fuel treatments in patterns, however, the most effective treatments were the dispersed and the regular patterns. From the results, we found that the cumulative effect of fuel treatment allocated on a large landscape could be influenced by the amount or the intensity of treatment activities implemented.

3.2 INTRODUCTION

As a result of the catastrophic fires that have occurred in forests of western North America over the last few decades, it has been suggested that fire suppression alone would be an unnatural management action for preserving forests in this region. Although fire suppression is needed to protect forests from wildfires, one consequence is the resulting extensive fuel loads, which make forests more vulnerable to wildfires. This has a compounded effect, since wildfires become more severe, decreasing the effectiveness of fire suppression activities. Therefore, the issue now is to recover forests back to healthy conditions through a combination of prescribed fire and management intervention spatially and temporally placed on the landscape.

Since the forests in this region have been shaped over the last 100 years by human activities that have had a commodity production emphasis, management strategies aimed at reducing fire risk have only recently begun to be investigated. Current research has focused on examination of various treatment activities to determine their effectiveness on reducing fire severity (Agee and Skinner, 2005; Pollet and Omi, 2002; Shang et al., 2004; Peterson et al., 2005; Stephens and Moghaddas, 2005b), and their influence on ecological damage and degradation (Huntzinger, 2003; Bury, 2004; Lee and Tietje, 2005; Stephens and Moghaddas, 2005a). In most of these studies, prescribed fire was suggested as the most acceptable fuel treatment, and indeed, it has been proven that fire behavior was most effectively disturbed in stands where prescribed fire was combined with other treatments such as mechanical thinning.

Mechanical thinning itself seems to have a limited influence on fire behavior and severity, but it could reduce fire severity when the treatments increase crown base height by removing small-diameter ladder trees rather than mid- or large-diameter trees (Agee and Skinner 2005).

Although fuel management treatments have been examined in several studies, the effects on fire behavior were tested at local scales. Since it would be virtually impossible to treat large landscapes and test hypotheses related to fire behavior, modeling has been suggested as a way to provide guidance in this area. Therefore, it is important to understand how individual fuel management treatments and their spatial and temporal pattern of implementation could affect progress of wildfire and its overall severity (Peterson et al., 2005; Kim et al., in review). Recently, Kim et al. (in review) developed a forest planning model based on a heuristic algorithm that schedules fuel treatment activities across both space and time, in which treatment activities were allocated in four patterns (dispersed, clumped, random, and regular pattern), and a harvest volume target would be evenly obtained through the time horizon. Kim et al. (in review) were able to achieve an even-flow harvest target, and generate the treatment patterns fairly well. However, in this previous research, overall fire severity was not much affected by the management alternatives (compared to the control solution). It was suggested additional prescriptions be considered, because the initial prescriptions focused only on controlling stand density through mechanical thinning, and no consideration was given to managing surface fuels. These initial prescriptions were considered typical operational practices. Therefore, in this research, fuel treatments that

have the intent of controlling ladder and surface fuels were developed and incorporated into the forest planning scheduling process.

The overall objective of this research was to optimize the pattern of fuel management activities across space and time using a heuristic scheduling process, and to understand cumulative effects of fuel treatments on the wildfire behavior. The hypothesis was that management alternatives with fuel treatment activities would be more effective in altering fire behavior or reducing fire severity compared to the control solution with no-treatment. The other main objective of the study was to determine the impact of two different intensities of overall scope of operation make any difference in the reduction in fire severity. While the prescriptions employed are aimed at controlling stand density and reducing certain types of fuels, this is measured by the desired timber volume level. One of our assumptions in this landscape analysis is that fuels management treatments are to be distributed across the landscape, and that they are not necessarily self-supporting (through associated revenues). Therefore, the amount of activity may be limited, but the spatial location important. Another hypothesis was that the intensity of fuels management activity on the landscape will not vary fire behavior much, as long as a moderate amount of treatments are scheduled.

3.3 METHOD

3.3.1 Study Site and Data Preparation

The Upper Grand Ronde River basin (approximately 178,000 hectares, Figure 3.1) in northeastern Oregon (USA) is the study site for this research. Most of the area is managed by the USDA Forest Service (Wallowa-Whitman National Forest), but small parcels of private forestlands are also situated in the basin.

Geographic Information System (GIS) databases representing forest structure were obtained from the Interior Northwest Landscape Analysis System (INLAS) project (http://www.fs.fed.us/pnw/lagrande/inlas/index.htm). These databases contained vector polygons and associated attributes to describe initial forest condition and forest strata. Forest inventory data (tree lists) were also obtained from the INLAS project, and are associated with each polygon based on the forest strata attribute. Centroids of management units were generated by using ArcView software, and utilized for a proxy for their locations. This spatial information is required for the scheduling process.

Two stand-level optimal prescriptions were generated using a growth and yield model (SLOMO) developed in previous research (Bettinger et al., 2005). The prescriptions were designed to maintain a desired stand density target (35 to 55% Stand Density Index) mainly by thinning small-diameter trees (< 7 or 10 inch) from stands. The changes in stand structure over 10 ten-year periods (100 years) using the prescriptions were provided by the SLOMO simulations. These prescriptions were not subsequently modified to reflect an additional prescribed fire treatment.

Two other prescriptions of 'thinning followed by prescribed fire' were produced by modifying the original two prescriptions with the following assumptions: 1) prescribed fires were assumed to be implemented within the same period of thinning, and 2) all surface fuels less than 2-meters in height were assumed killed (van Wagtendonk, 1996; Stephens, 1998). Using these assumptions, all trees less than 2-meters in height were removed from the given SLOMO outputs in the period of treatment. In addition, it was assumed that once a tree has vanished by a fire in a certain management period, it could not exist in any post-fire periods. Thus, trees with the same tree indices that were removed in the period of treatment were also removed in the following management periods. Subsequently, five prescriptions (including a prescription with no treatment) were utilized.

3.3.2 Scheduling of Spatial Patterns of Fuel Management Activities

Four spatial patterns of activity were modeled (dispersed, clumped, random, and regular patterns). To optimize the pattern of treatments across space and time, a scheduling process was established based on a heuristic modeling technique: the Great Deluge Algorithm (GDA). GDA was introduced by Dueck (1993) and has been applied to forest planning problems in Bettinger et al. (2002), Kim and Bettinger (2005), and Kim et al. (in review). The objective function of the scheduling model includes a commodity production component (maximize even-flow) and a spatial pattern component. These are described shortly.

In Bettinger et al. (in press), a maximum even-flow harvest volume (200,716 MBF per decade) was determined using linear programming with simplified management assumptions (i.e., no spatial constraints were considered and continuous variables were used to represent choices assigned to management units). They intended to achieve even-flow of the maximum target volume using operational prescriptions in which large diameter trees would be harvested. This harvest level was computed under the assumption that intensive and extensive activity would be allowed in the watershed, and thus the resulting harvest level should be viewed as an upper bound on the productive capacity of the resource. In today's management environment, we are assuming a much lower level of activity will be allowed. Thus, since a spatial constraint is considered in this research, and harvesting is directed at small diameter trees, the target volume should be selected from values less than the theoretical maximum. In fact, there is no standard or criterion specified for determining a harvest volume target available from ladder fuel reduction. Therefore, it is necessary to test several target volumes to determine the most appropriate harvest level for both patterning treatments and obtaining an even-flow volume during the entire management period. In this research, two target volumes were chosen from values much less than the theoretical maximum: a high volume target (10,000 MBF) and a low target volume (5,000 MBF).

With these target volumes, scheduling procedures were repeated 30 times for each pattern to find the best solution that spatially optimizes a desired pattern across landscape and achieve the even-flow volume. Each repetition started with a random schedule of treatment activities to make the resulting solutions independent. For

quantifying the effects of management solutions more accurately, a control solution with no treatment scheduled was also generated.

Dispersed Pattern of Fuel Management Activities

A dispersed pattern is generally depicted as a pattern in which management units are widely spread across landscape with minimum clustering. The ideal dispersed pattern in this research is assumed to maximize the mean of nearest neighbor distances, and also minimize deviations between actual harvest volume and the harvest volume target. The following objective function was developed to generate a pattern as close to the ideal pattern:

Minimize

$$\sum_{k=1}^{P}\left(\left|\sum_{i=1}^{N_k} H_{ik} - T\right|\right) - \sum_{k=1}^{P}\left(\frac{1}{N_k}\cdot\sum_{i=1}^{N_k} D_i\right) \qquad [1]$$

Where,

H_{ik} : Harvest volume from unit i in time period k (i = 1, 2,…, N_k, k = 1, 2, …, P)

T : Target volume of timber harvesting

D_i : Distance between the centroid of unit i and its nearest neighbor (i = 1, 2, …, N_k)

N_k : The set of management units scheduled for treatment in time period k

i : Index of management units scheduled for treatment

k : a time period

P : Total number of time periods ($P = 10$)

A scheduling model based on the above objective function seeks a solution that minimizes the difference between actual harvest volume and a harvest volume target, and maximizes the mean distances between each management unit scheduled for treatment and its nearest neighbor. While the basic application of GDA seeks a solution with a higher peak (higher objective function value) as water-levels (threshold value) increase, the solution optimized in this research was expected to have the minimum objective function value. Thus, the algorithm was modified to seek a solution with a lower bottom (lower objective function value) as water is discharged (Figure 3.2). Three stopping criteria were used in the modified version of GDA: total iterations, non-improved iterations, and water-level. Parameters associated with these stopping criteria are given in Table 3.1.

Clumped Pattern of Fuel Management Activities

A clumped pattern has clusters of treatment units on the landscape. The ideal clumped pattern in this research is assumed to minimize the mean of nearest neighbor distances and minimize the deviation between actual harvest volume and a harvest volume target. While the dispersed pattern is expected to maximize the mean of nearest neighbor distances, the clumped pattern is expected to minimize it. To accept this

distinction, equation 1 was simply modified by adding the two portions of the objective function as follows:

Minimize

$$\sum_{k=1}^{P}\left(\left|\sum_{i=1}^{N_k} H_{ik} - T\right|\right) + \sum_{k=1}^{P}\left(\frac{1}{N_k}\cdot\sum_{i=1}^{N_k} D_i\right) \qquad [2]$$

A scheduling procedure with this objective function seeks a solution that minimizes the difference between actual harvest volume and harvest volume target and also minimizes the mean of nearest neighbor distances. The scheduling process for optimizing the clumped pattern was basically the same with that of dispersed pattern (Figure 3.2), but some of the parameters related to the stopping criteria – initial water level and minimum water level – were adjusted based on trial runs of the scheduling model (Table 3.1).

Random Pattern of Fuel Management Activities

In a random pattern, management units are randomly distributed across landscape. Within the GDA scheduling process, management units are randomly chosen and prescriptions are also randomly chosen and assigned to them. Thus, solutions generated within this process were assumed to have a random pattern, and the objective function was simply modified by dropping the latter portion of equation 1 as follows:

Minimize

$$\sum_{k=1}^{P}\left(\left|\left(\sum_{i=1}^{N_k} H_{ik}\right)-T\right|\right) \qquad [3]$$

Since dispersion of management units was not considered, a solution would be evaluated according to the deviation of actual harvest volume and the harvest volume target. However, from test trials, it was found that solutions resulted from the scheduling process with this objective function were limited to provide a statistically valid pattern of treatments. Thus, the point pattern analysis technique, which is a statistical approach to assess a pattern of points distributed across a landscape, was applied to present more reliable management solutions. One of the statistics associated with this analysis (z-statistic) was adopted as a management constraint for optimizing random pattern as followings:

Subject to

$$|z| < R \qquad [4]$$

Where:

z : z-statistic of the point pattern analysis

R : z-value for complete randomness at 95% confidence level (= 1.96)

A solution which has an acceptable value of this statistic could be verified as a random pattern through the point pattern analysis. Thus, to present statistically valid random pattern of treatments, solutions generated during the scheduling process were evaluated, and, if a solution did not qualify as a randomly spaced solution, it was not saved. The scheduling process was modified with this constraint for the random pattern (Figure 3.3).

Regular Pattern of Fuel Management Activities

A regular pattern would rarely be found in a natural landscape, because it is generally defined as the optimum dispersed pattern. In Kim et al. (in review), a regular pattern was assumed to be an artificial pattern, in which treatment activities are systematically arranged across landscape with a constant spatial interval. Ideally, treatment units in the regular pattern were expected to have same distance to four neighbor units (northern, southern, eastern, and western). The 'interval' was considered as a desired distance between centroids of treatment units that produces an ideal regular pattern. To generate the ideal pattern, Kim et al. (in review) developed a unique approach for dispersing treatment units.

Here, management units are chosen prior to assigning prescriptions to the units, and then a feasible set of prescriptions for selected management units was assigned to them. Since the pattern of treatment units was decided prior to assigning a prescription, dispersion of management units is not an essential element in the objective function. In addition, according to the given prescriptions, a unit scheduled for treatment in a certain

time period is able to be scheduled for treatment again in a following period. This suggests that a set of prescriptions assigned to management units for one time period could influence scheduling of other following time periods. For this reason, a solution that guarantees a nearly perfect regular pattern in across time periods is rarely obtained. Therefore, the scheduling process seeks a solution that optimizes the objective function value based on selected management units in the first time period. Based on these limitations, the objective function was modified as below:

Minimize

$$\left| \left(\sum_{i=1}^{N} H_{i1} \right) - T \right| \qquad [5]$$

Since the most efficient spatial interval between management units for reducing the fire damage was not currently specified, several intervals were tested. According to the Kim et al. (in review), the interval (distance) between management units affected not only their dispersion, but even-flow harvest as well. Thus, in this research, a set of various intervals (2.5, 3.0, 3.5, 4.0, 4.5, and 5.0 kilometer) was used for developing systematic points during the scheduling process and the most appropriate interval was given from the best solution that achieved the closest harvest to the volume target. Therefore, the scheduling process of a regular pattern was modified (Figure 3.4) for accepting systematic allocation with the various spatial intervals.

3.3.3 Point Pattern Analysis: Nearest Neighbor Distance

In Kim et al. (in review), the scheduling model provided a limited result for optimizing the spatial pattern of management activities, even though it successfully achieved even-flow of harvest volume target. To validate the patterns of treatment units, Kim et al. (in review) adopted the nearest neighbor distance analysis, which is one of point pattern analysis techniques (Boots and Getis, 1988; Cressie, 1993). The mean of nearest neighbor distance observed between treatments were compared to the following statistic, which estimates the expected mean of nearest neighbor distance for a pattern with complete randomness:

$$d_{\exp} = 0.5\sqrt{\frac{A}{N}} \qquad [6]$$

Where:

d_{exp} : Expected mean distance of nearest neighbor for complete random pattern

A : Area

N : Number of scheduled management units

The hypothesis in the point pattern analysis is that a pattern would be random if the observed mean of nearest neighbor distance was not significantly distinct from the expected mean of complete randomness. If the observed mean was significantly less than the expected mean, the pattern would be considered clustered; if it was

significantly larger, the pattern would be considered dispersed. The significance of difference between observed and expected mean was tested by using a z-statistic at the 95% confidence level:

$$z = \left[\frac{\hat{d}_{obs} - d_{\exp}}{\sqrt{\mathrm{var}(\hat{d})}} \right] \qquad [7]$$

Where:

$\hat{d}_{obs}$: Observed mean distance of nearest neighbor

$\mathrm{var}(\hat{d})$: Variance $\left(= 0.0683 \times A/N^2 \right)$

As mentioned in the part of scheduling patterns, a similar nearest neighbor distance calculation was adopted into the objective function of dispersed and clumped pattern. Thus, the pattern optimized from these scheduling processes is expected to be verified for the desired pattern. However, because the mean of nearest neighbor distance was not considered within the objective function for random pattern, solutions resulted from scheduling process rarely achieve statistical validation for random pattern through the nearest neighbor distance analysis. Therefore, the z-statistic noted above was adopted as a constraint to evaluate solutions generated during this scheduling process.

3.3.4 Fire Growth Simulation

FARSITE (Finney, 1998) is a fire growth simulation model widely used by several federal government and state land management agencies, and has been utilized in several research projects (van Wagtendonk, 1996; Stephens, 1998; Finney, 2001; Finney, 2003; Stratton, 2004). In this research, FARSITE was used to model fires, and to quantify changes in fire behavior differentiated by fuel treatment activities or patterns of their dispersion. FARSITE requires spatial information on topography and fuel conditions for input. These input files should have an ASCII raster file format, so inputs of topography (elevation, slope, and aspect) were prepared using GIS software. Since fuel conditions are influenced by solutions generated by the scheduling processes, it is necessary to prepare ASCII raster input files of fuel conditions (fuel type, canopy cover, stand height, and crown base height) for each solution separately. Therefore, the scheduling model was designed to automate the data preparation of such fuel conditions, and as a result, the generation of inputs associated with running FARSITE was seamless without using GIS software. Along with spatial inputs for topography and fuels, FARSITE also requires weather conditions in text file format. A sample set of weather conditions (temperature, humidity, wind, and moisture) given for a hypothetical extreme fire season in eastern Oregon was utilized for the simulation.

Although FARSITE supports several kinds of outputs describing a simulated fire and its behavior, fireline intensity and flame length were primarily used for comparison of treatment effects. To compare the treatment effects according to the patterns, fires with 15 different ignition points were simulated along with a set of inputs of each

pattern, and then the resulting average flame length and average fireline intensity were recorded. The 15 ignition points were selected randomly and applied consistently to every simulation (i.e., the same ignition points were used in each simulation) of the four patterns and the control solution.

3.4 RESULTS AND DISCUSSION

3.4.1 Spatial Pattern of Fuel Management Activities

The best solutions generated by the scheduling model could optimize each spatial pattern of fuel management activities fairly well. The pattern of management units scheduled for treatments in the first time period are depicted in Figure 3.5 (low target volume) and Figure 3.6 (high target volume). Because the private land in the center of the study site consisted of a large meadow, management units on the private land were rarely selected for treatment. Although the lack of treatment in the private land degraded optimization of patterns, each pattern was clearly verified in visual. Moreover, the point pattern analysis that is based on the nearest neighbor distance provided a statistical verification for patterning treatments. According to results of the point pattern analysis (Table 3.2), the optimized solutions scheduled for the low target volume were all validated for the desired patterns. The solutions scheduled for the high target volume were also validated for most of the desired patterns, except the dispersed pattern.

From the scheduling process, it was found that scheduling a dispersed pattern requires more simulation time than other patterns. Especially, in scheduling a dispersed pattern for the high target volume, it took a huge amount of simulation time (143 ¼ hours). A better solution that provides a statistically valid dispersed pattern might be achieved by adjusting GDA stopping criteria. However, it would not be efficient because adjusting stopping criteria might increase the simulation time up to an enormous level. In addition, with increased management treatment units, the dispersed pattern becomes less distinct, and more like the random pattern, which the point pattern analysis shows.

The point pattern analysis was made using the average number of treatment units and the average of observed nearest neighbor distances across the time horizon. Therefore, even though the overall pattern was acceptable, a pattern might be invalid in a certain period of time. The variance of the z-statistics derived from the point pattern analysis in each time period is illustrated in Figure 3.7 (low target volume) and Figure 3.8 (high target volume). As shown in the figures, z-statistics of each pattern fluctuate across the time horizon, and some of them deviate out of the valid range of desired patterns. For example, the best solution scheduled for the dispersed pattern with low target volume does not represent a valid pattern in periods 1 and 3, while the solution of the random pattern with low target volume was not valid in periods 5 and 6 (Figure 3.7). The best solution scheduled for the random pattern with high target volume does not represent a valid pattern in the middle and the latter portion of time horizon either

(Figure 3.8). Even though there is periodic variation, the distributions of z-values were fairly well distinct for each pattern.

3.4.2 Even Flow of Harvest Volume

The best solutions of the four spatial patterns simulated a successful even-flow harvest level for both low and high target volumes (Table 3.3). Harvest volumes of all solutions are very close to the target volume across the entire time horizon. Thus, this result proved that the scheduling model developed in this research modeled an even-flow constraint appropriately. In Kim et al. (in review), the scheduling model they developed had a tendency to increase the number of treatment units when optimizing the dispersed pattern. The same tendency was also found in this research (Table 3.4). The number of treatment units scheduled for the dispersed pattern was almost a double compared to other patterns. Therefore, this might be an issue if other economic or environmental concerns arise in scheduling fuel treatments.

3.4.3 Fire Simulations

The results of fire simulations are summarized in Table 3.5. According to the simulation results, in most cases fire behavior was effectively altered by treatment activities scheduled using both the high and low target volume. The treatment activities were most effective when they were spatially optimized in the dispersed or the clumped pattern. Most treatments marginally reduced the flame length and fireline intensity, which indicate the severity of fires. The simulation results showed that the regular pattern was most effective in this regard, even though the pattern was not guaranteed in

the entire time horizon. The dispersed and clumped patterns reduced overall fire size the most.

Rothermel and Rinehart (1983) have introduced an interpretation of fire behavior, in which fire behavior, such as flame length and fireline intensity, were classified into four severity classes (Table 3.6). The interpretation was originally developed for consideration of fire suppression, but it provided a good interpretation of fire behavior and severity as well. Among the given four classes, class 3 and 4 were considered as the severe fire classes, and a fire in these classes were assumed not to be controlled by suppression efforts.

In this research, it was expected that the fuel treatment activities could reduce the areas where fire severity were classified in such severe behavior classes given by Rothermel and Rinehart (1983). Because the fire simulation outputs have a grid-raster GIS file format, the number of fire grid cells – each grid cell has a 30 × 30 meter size – were counted and summarized for the fire behavior classes (Table 3.7). Then, the number of fire grid cells in severe fire behavior classes (class 3 and 4) were summed for comparison of treatment effects on fire severity. Figure 3.9 shows the sum of fire grid cells in severe classes summarized from the simulated results of flame length, while Figure 3.10 shows the sum of the simulated results of fireline intensity. The number of fire grid cells in the severe behavior classes showed a similar tendency in both Figure 3.9 and 10, though of using different fire behaviors. Compared to the control solution, the treatment activities scheduled in four spatial patterns were all effective in reducing the severe fire behavior classes no matter what the harvest target volume. Among the

four spatial patterns, however, the dispersed pattern stood out under the low volume harvest, and the dispersed and regular patterns were most effective under the high volume target. The clumped pattern was more effective than the random pattern, and the treatments scheduled in a random pattern could not provide significant effects compared to other patterns.

To present a reason that could explain the difference in treatment effects by patterning, the fire simulation output were investigated again, but at this time, the fire grid cells were classified into the following three categories: grid cells in treatment units, grid cells adjacent to treatment units (4 neighbor grid cells), and grid cells outside treatment units. Fires are supposed to have more chances to contact treatments when they are scheduled in a pattern which was proved above to effectively reduce fire severity. Thus, the number of grid cells classified in these three categories was summarized for the comparison of patterning effects (Table 3.8). According to the Table 3.8, simulated fires could contact to the treatments most often when treatments were scheduled for the dispersed pattern. This result supported the fact that treatment activities scheduled in the dispersed pattern could degrade fire severity because fires had more chance to be influenced by treatments.

According to the fire behavior classification described above, the regular pattern optimized for the high target volume was most effective in reducing the number of fire grid cells in severe behavior classes. However, the number of grid cells affected by treatments was even less than that of dispersed pattern. This fact implies that fuel treatment activities scheduled in the regular pattern were more intensively implemented

within the management units. That is to say, because it is necessary to produce a similar amount of timber from the less number of management units (Table 3.4), the thinning activities scheduled for the regular pattern should be more intensive than those for the dispersed pattern.

3.5 CONCLUSIONS

The modeling efforts developed in this research presents a unique application of spatial modeling concepts to the planning of fuel management activities. The solutions generated by the scheduling model provided spatially optimized allocation of treatment activities across a large landscape, but also evenly distributed the harvest volume through the multi-decade time horizon. The patterns of treatments allocated across the landscape were not only verified in a visual assessment, and also found statistically valid for each desired pattern.

Two types of prescriptions were used in this research: ‘thinning’ and ‘thinning followed by prescribed burning’. The thinning activities were aimed at controlling the stand density, but the ladder trees in the small-diameter range are the primary target of the treatment. According to the fire simulation results, the cumulative effects of the fuel treatment implemented by these prescriptions could alter fire behavior or its severity. However, the treatment itself was not enough to explain the differentiation of the cumulative effects of treatments that were scheduled for each spatial pattern. The results

showed that fuel treatments were most effective when they were scheduled in the dispersed pattern which spread a larger amount of treatments on the landscape, and regular pattern in which more aggressive thinning activities would be implemented. Therefore, it is suggested that the amount of treatment or intensity of the activities would be the real issues in scheduling fuel treatments that essentially disrupt behavior of wildfires burning a large landscape. However, the thinning activities used in this research focused on removing small diameter trees from stands, thus harvested timber would not be as much commercial and might not guarantee enough revenue due to treatment costs. Therefore, economical issues should be concerned when increasing the amount of fuel treatments along with the current treatment prescriptions.

This research provided a more advanced scheduling model which enables a forest planner or managers to adopt the concept of spatial optimization of fuel management, but it still has some limitations. First of all, the prescriptions used in this research were originally developed for maintaining a desired stand density target (35 ~ 55% Stand Density Index) by thinning out ladder trees from small-diameter range (< 7 or 10 inch) from stands. Although prescriptions of 'thinning followed by prescribed fire' activities were generated modifying the original thinning prescriptions, one of assumptions involved might not be acceptable. For example, prescribed fire was assumed to burn down all trees less than 2 meter in height, but this might not be guaranteed. Therefore, the results of this research would be enhanced by using more feasible prescriptions for fuel conditions.

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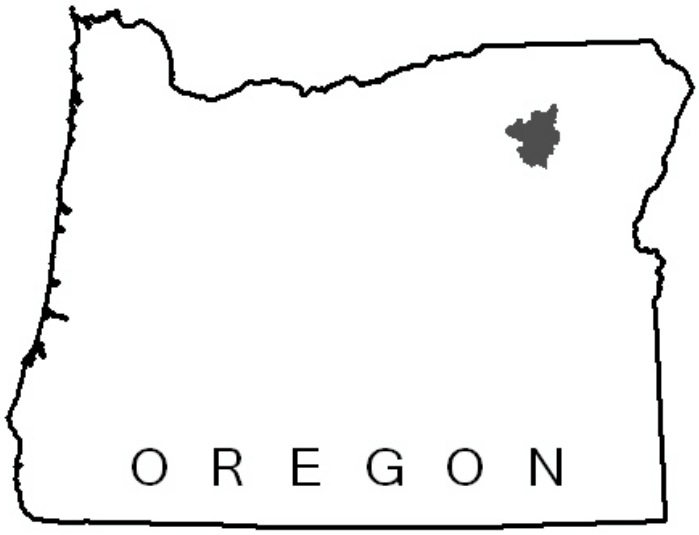

Figure 3.1 – Study site: Upper Grand Ronde River basin in eastern Oregon (USA)

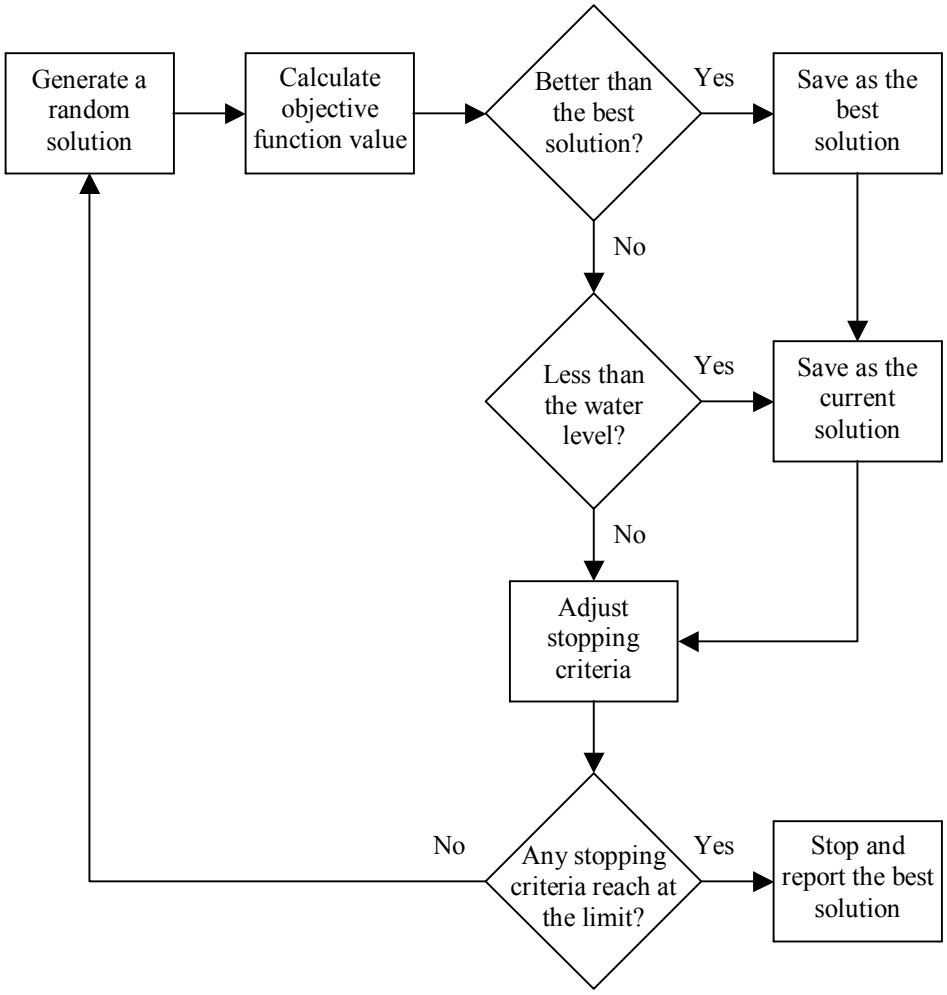

Figure 3.2 – Flowchart of GDA scheduling processes for dispersed and clumped patterns

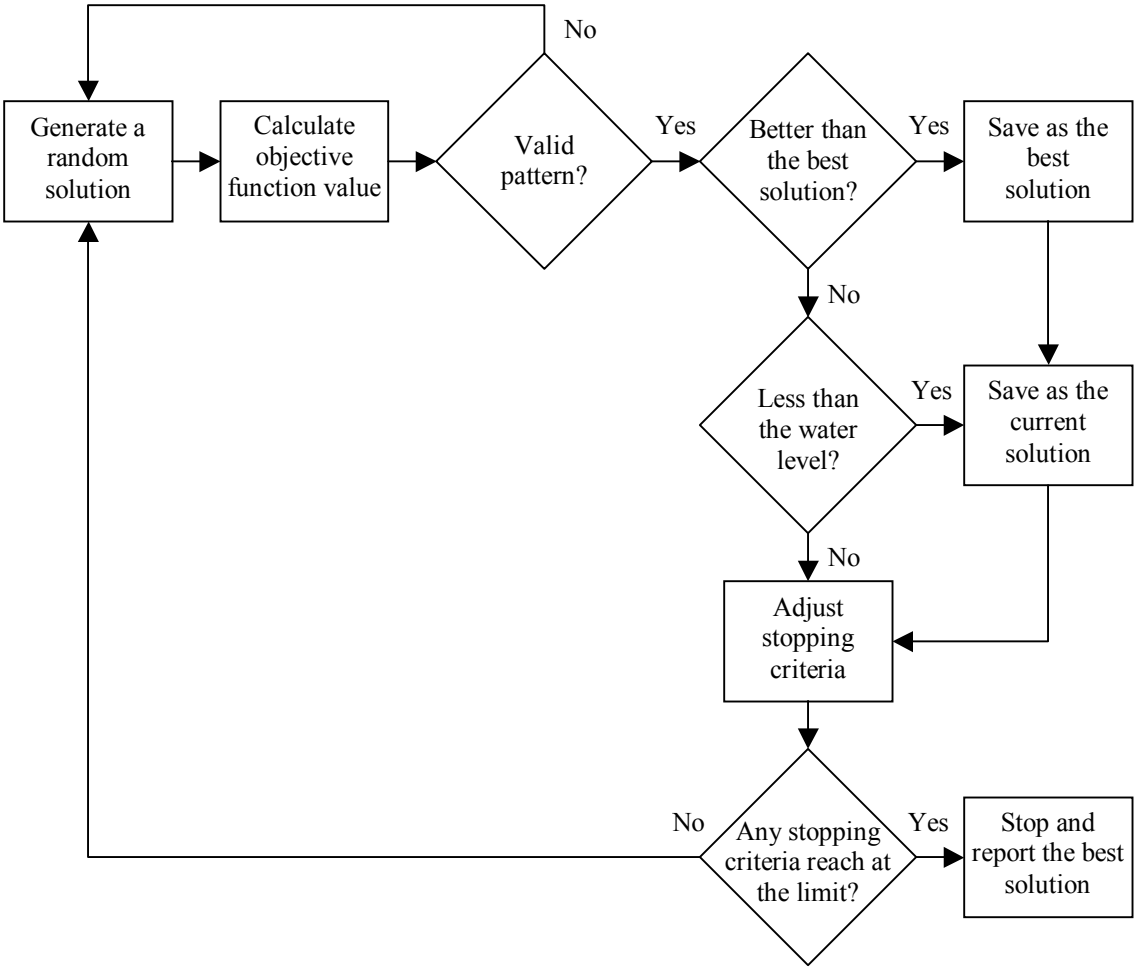

Figure 3.3 – Flowchart of GDA scheduling process for random patterns.

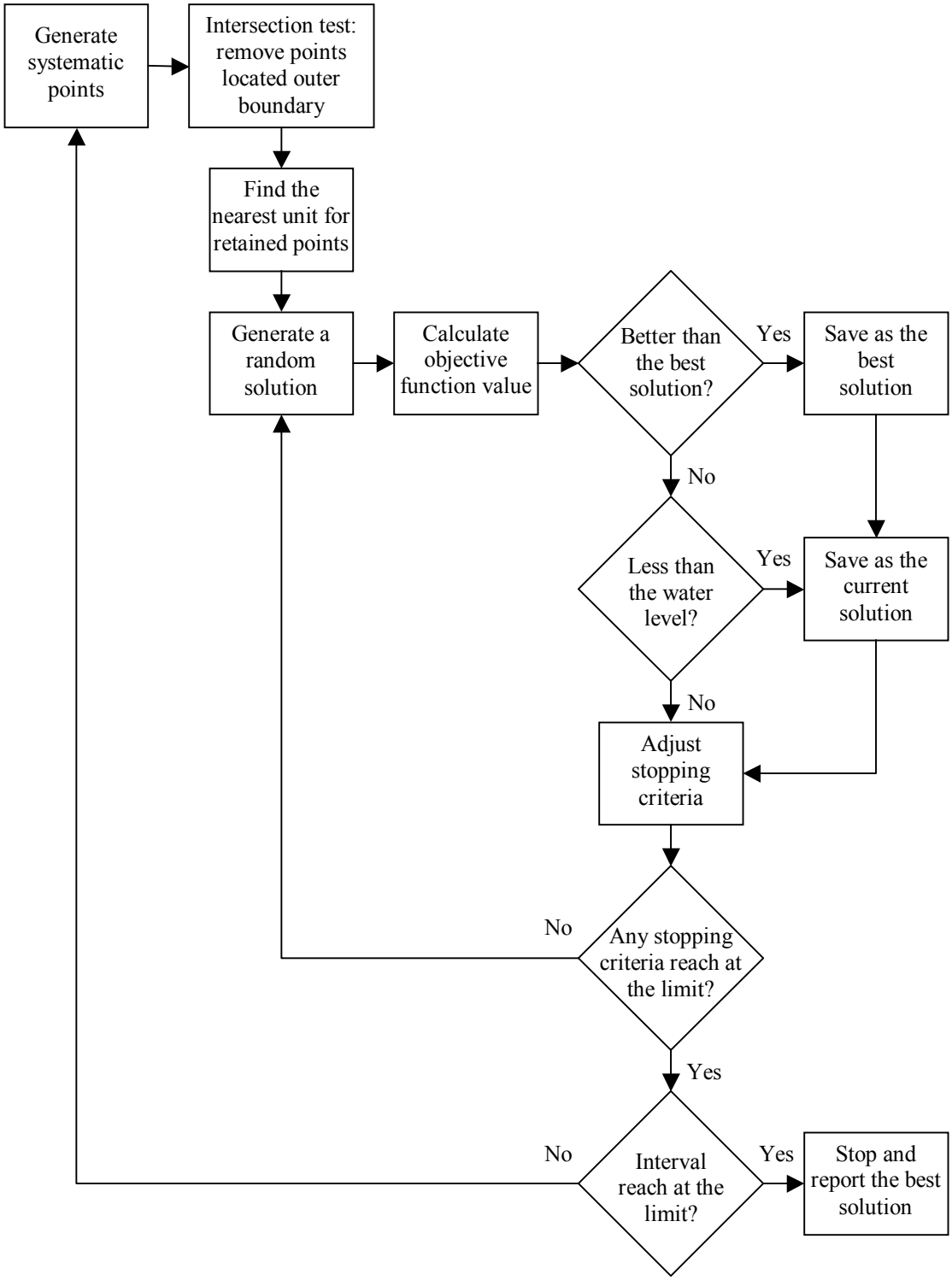

Figure 3.4 – Flowchart of GDA scheduling process for regular pattern

Figure 3.5 – Optimized spatial patterns of treatment units in the first time period (low target volume)

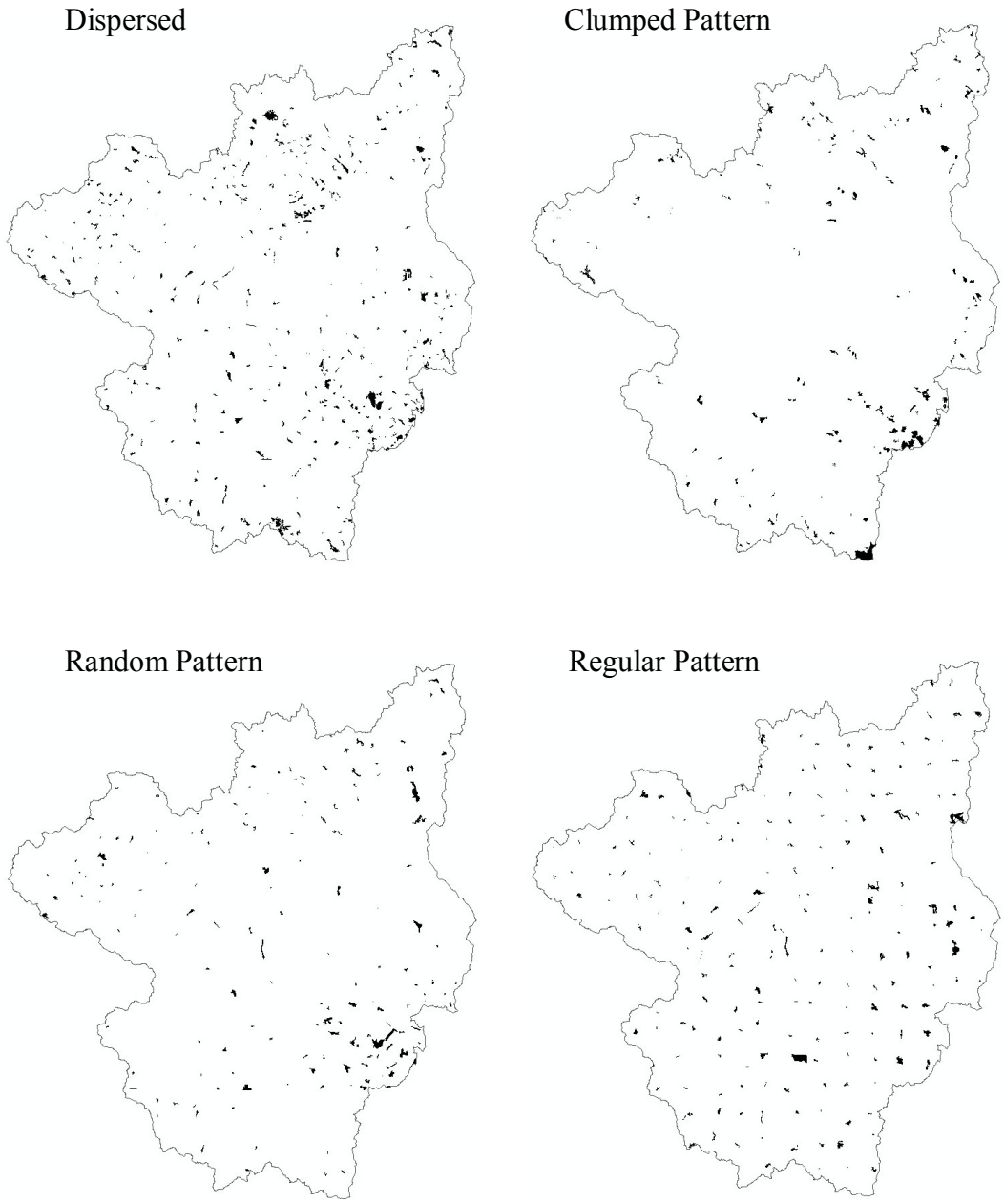

Figure 3.6 – Optimized spatial patterns of treatment units in the first time period (high target volume)

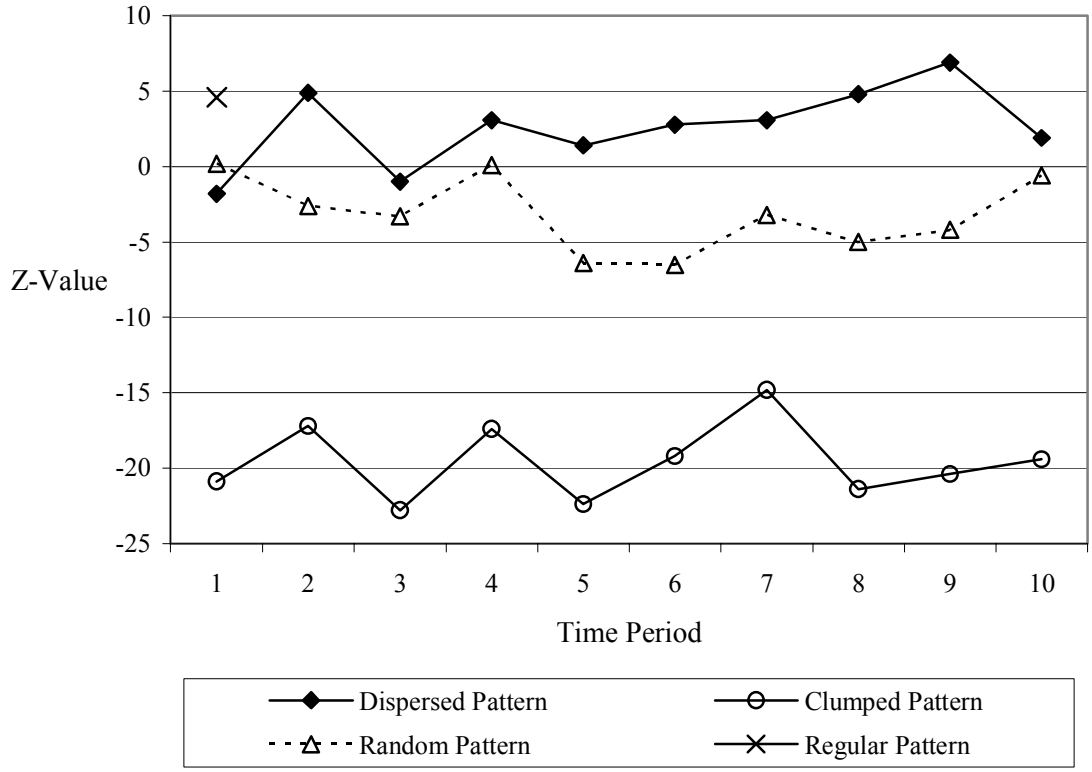

Figure 3.7 – Z-statistics resulted from point pattern analysis (low target volume)

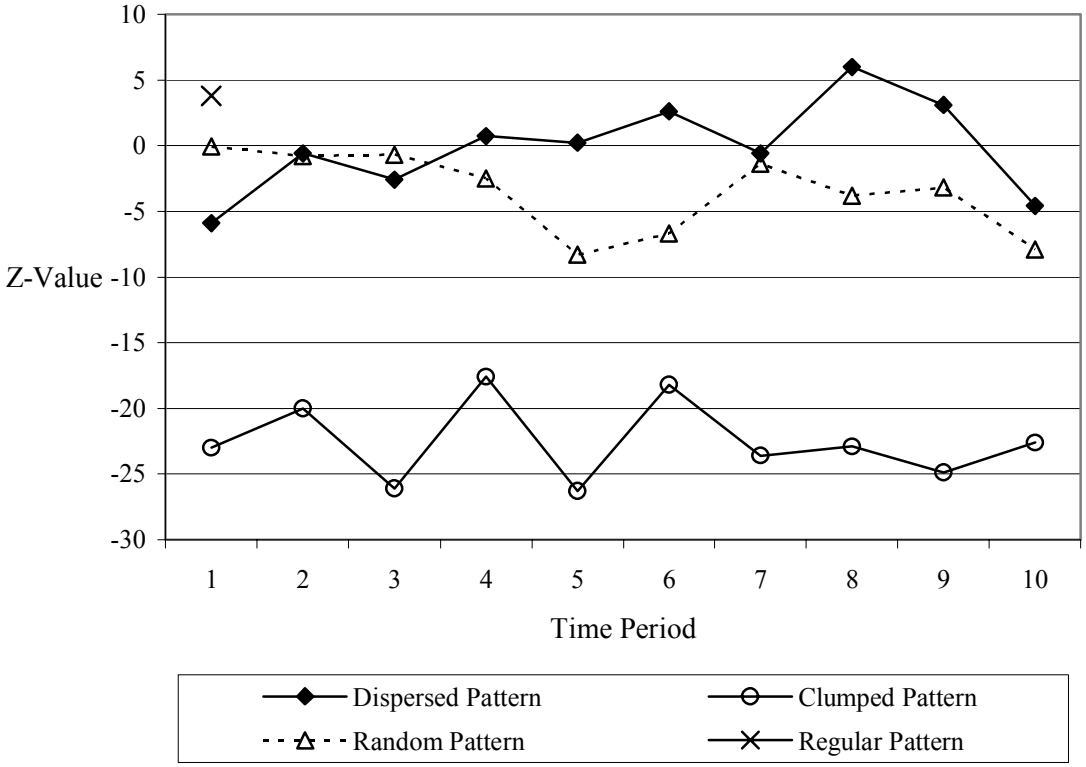

Figure 3.8 – Z-statistics resulted from point pattern analysis (high target volume)

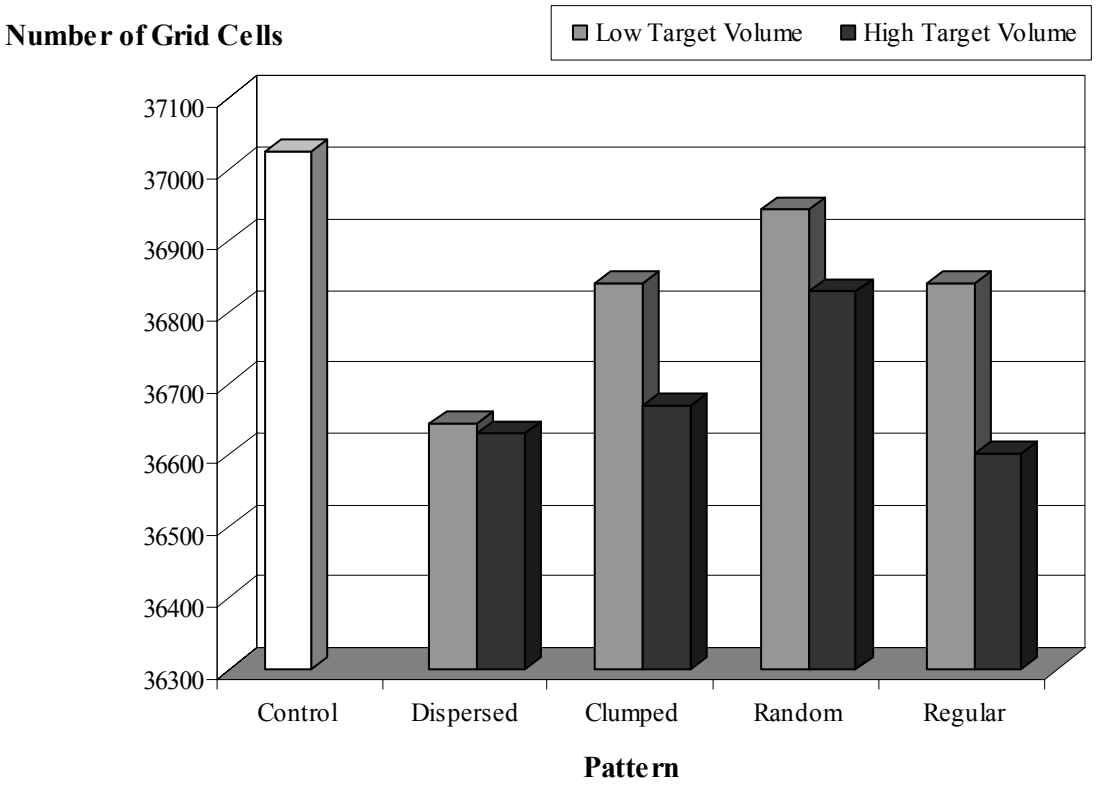

Figure 3.9 – Number of fire grid cells in the severe fire behavior classes: flame length

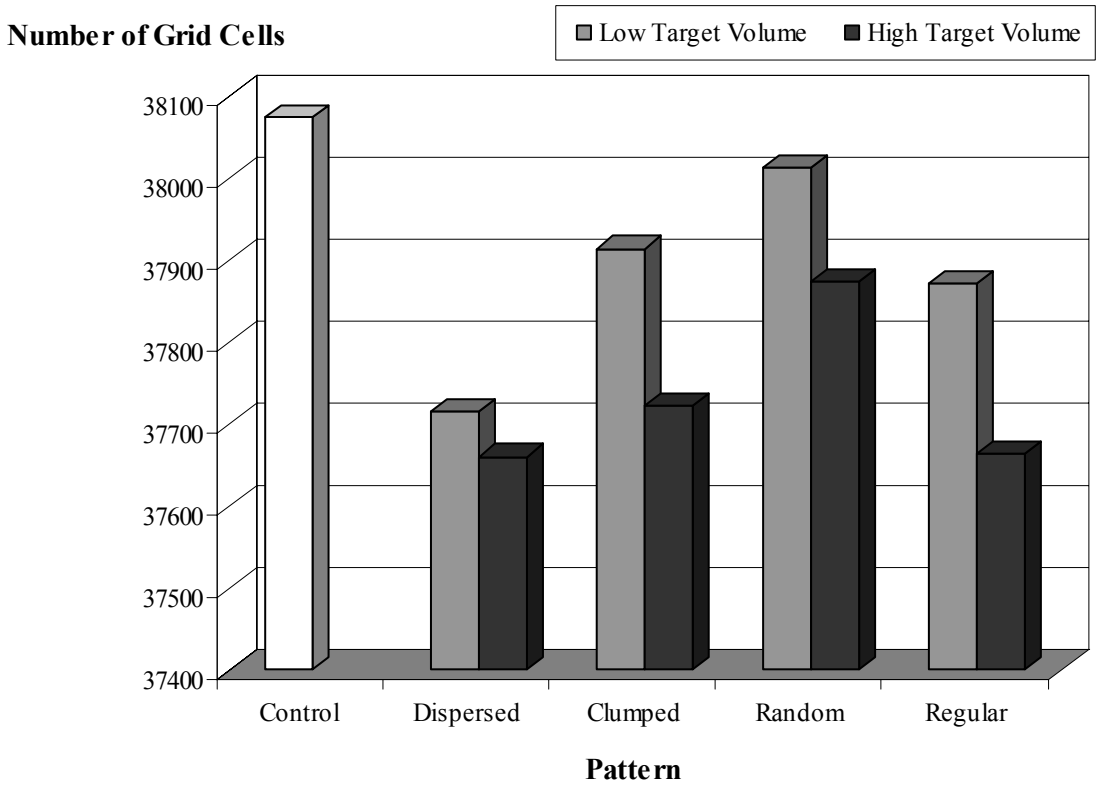

Figure 3.10 – Number of fire grid cells in the severe fire behavior classes: fireline intensity

Table 3.1 – Parameters associated with stopping criteria for each scheduling process

Parameters	Dispersed Pattern	Clumped Pattern	Random Pattern	Regular Pattern
Low Target Volume				
Total iterations	100,000	100,000	100,000	10,000
Non-improved iterations	50,000	50,000	50,000	5,000
Initial water-level	10,000,000	20,000,000	5,000,000	1,000,000
Discharging speed	0.001	0.001	0.001	0.001
Minimum water-level	-10,000,000	0	0	0
Upper limit of interval	-	-	-	4,500
Lower limit of interval	-	-	-	2,500
High Target Volume				
Total iterations	150,000	150,000	150,000	10,000
Non-improved iterations	100,000	100,000	100,000	5,000
Initial water-level	10,000,000	20,000,000	15,000,000	1,000,000
Discharging speed	0.001	0.001	0.001	0.001
Minimum water-level	-10,000,000	0	0	0
Upper limit of interval	-	-	-	4,000
Lower limit of interval	-	-	-	2,000

Table 3.2 – Results of point pattern analysis for optimized spatial patterns of fuel treatments: validation for overall average across the time horizon

Test Statistics	Dispersed Pattern	Clumped Pattern	Random Pattern	Regular Pattern
Low Target Volume				
Number of Treatment Units	446	182	217	142
Observed Mean*	1,102	374	1,334	2,128
Expected Mean* of the randomness	999	1,565	1,433	1,772
z-statistic	4.2	-19.6	-1.9	4.6
Validation	Valid	Valid	Valid	Valid
High Target Volume				
Number of Treatment Units	591	264	346	191
Observed Mean*	878	360	1,073	1,748
Expected Mean* of the randomness	868	1,299	1,135	1,527
z-statistic	0.5	-22.5	-1.9	3.8
Validation	Invalid	Valid	Valid	Valid

* Mean distance (meter) between treatment units and their nearest neighbor

Table 3.3 – Harvest volume (MBF) of the optimized solution for each spatial pattern

Management Period	Dispersed Pattern	Clumped Pattern	Random Pattern	Regular Pattern
Low Target Volume				
Period 1	5,000	5,000	5,000	5,000
Period 2	4,998	5,003	5,000	-
Period 3	5,002	5,000	5,000	-
Period 4	5,000	5,000	5,000	-
Period 5	5,001	4,998	5,000	-
Period 6	4,999	5,001	5,000	-
Period 7	4,999	5,000	5,000	-
Period 8	5,001	5,000	5,000	-
Period 9	5,000	5,000	5,000	-
Period 10	5,000	5,000	5,000	-
High Target Volume				
Period 1	10,002	10,000	10,000	10,000
Period 2	10,004	10,000	10,000	-
Period 3	10,003	10,000	10,000	-
Period 4	10,002	10,000	10,000	-
Period 5	10,007	10,000	10,000	-
Period 6	10,003	10,000	10,000	-
Period 7	10,008	10,000	10,000	-
Period 8	10,010	10,000	10,000	-
Period 9	10,000	10,000	10,000	-
Period 10	10,002	10,000	10,000	-

Table 3.4 – Number of treatment units of the optimized solution for each spatial pattern

Management Period	Dispersed Pattern	Clumped Pattern	Random Pattern	Regular Pattern
Low Target Volume				
Period 1	329	169	117	142
Period 2	249	132	164	
Period 3	439	216	197	
Period 4	334	156	155	
Period 5	478	246	260	
Period 6	411	240	272	
Period 7	477	115	236	
Period 8	800	196	297	
Period 9	575	185	265	
Period 10	373	170	207	
High Target Volume				
Period 1	456	215	174	191
Period 2	333	265	278	
Period 3	559	318	319	
Period 4	459	216	302	
Period 5	720	306	387	
Period 6	769	210	420	
Period 7	580	260	264	
Period 8	876	241	368	
Period 9	643	272	404	
Period 10	518	340	544	

Table 3.5 – Fire simulation results of the optimized solutions: fifteen fires in the fire time period

Fire Behavior	Control	Dispersed Pattern	Clumped Pattern	Random Pattern	Regular Pattern
Low Target Volume					
Flame Length (feet)	3.571	3.563	3.570	3.569	3.562
Change from control	-	(-0.008)	(-0.001)	(-0.002)	(-0.009)
Fireline Intensity (Btu/ft/s)	177.935	177.264	177.871	177.696	177.133
Change from control	-	(-0.671)	(-0.064)	(-0.234)	(-0.802)
Fire Size (acre)	78,812	78,474	78,542	78,690	78,677
Change from control	-	(-338)	(-270)	(-122)	(-135)
High Target Volume					
Flame Length (feet)	3.571	3.563	3.563	3.565	3.558
Change from control	-	(-0.008)	(-0.008)	(-0.006)	(-0.013)
Fireline Intensity (Btu/ft/s)	177.935	177.297	177.374	177.543	176.671
Change from control	-	(-0.638)	(-0.561)	(-0.392)	(-1.264)
Fire Size (acre)	78,812	78,414	78,356	78,830	78,696
Change from control	-	(-398)	(-456)	(+18)	(-116)

Table 3.6 – Interpretation of Fire Behavior*

Classes	Flame Length	Fireline Intensity (Btu/ft/s)	Interpretations
1	< 1.2 m (< 4 ft)	< 100	Fires can generally be suppressed by persons using hand tools at the head or flanks
2	1.2 ~ 2.4 m (4 ~ 8 ft)	100 ~ 500	Fires are too intense for direct suppression on the head by persons using hand tools. Equipment or vehicles would be required for suppression, but effective.
3	2.4 ~ 3.4 m (8 ~ 11 ft)	500 ~ 1000	Fires may start torching out, crowning and spotting. Suppression at the fire head is probably ineffective to control fires.
4	3.4 m < (11 ft <)	1000 <	Crowning and spotting would be occurred. Suppression efforts at the fire head are ineffective.

* Source: Rothermel and Rinehart (1983)

Table 3.7 – Fire simulation results by the fire behavior class: number of grid cells in each fire behavior classes

Fire Behavior Classes			Control	Dispersed Pattern	Clumped Pattern	Random Pattern	Regular Pattern
Flame Length	Low Target Volume						
		Class 1	253,448	252,445	252,444	253,004	253,526
		Class 2	63,907	63,768	63,881	63,884	63,408
		Class 3	21,854	21,742	21,731	21,822	21,810
		Class 4	15,172	14,903	15,110	15,122	15,029
	High Target Volume						
		Class 1	253,448	252,185	252,375	253,508	253,563
		Class 2	63,907	63,775	63,283	64,124	63,692
		Class 3	21,854	21,672	21,657	21,737	21,594
		Class 4	15,172	14,957	15,012	15,091	15,009
Fireline Intensity	Low Target Volume						
		Class 1	244,200	243,282	243,231	243,661	244,044
		Class 2	72,106	71,860	72,020	72,158	71,857
		Class 3	21,786	21,655	21,718	21,776	21,760
		Class 4	16,289	16,061	16,197	16,237	16,112
	High Target Volume						
		Class 1	244,200	243,219	243,166	244,300	244,335
		Class 2	72,106	71,709	71,438	72,285	71,859
		Class 3	21,786	21,621	21,625	21,642	21,533
		Class 4	16,289	16,040	16,098	16,233	16,131

Table 3.8 – Number of fire grid cells affected by treatment activities scheduled for each pattern

	Dispersed Pattern	Clumped Pattern	Random Pattern	Regular Pattern
Low Target Volume				
In Treatment Units	3,652	986	875	1,685
Adjacent to Treatment Units	3,083	1,088	922	1,610
Outside Treatment Units	346,123	351,092	352,035	350,478
Total fire grid cells	352,858	353,166	353,832	353,773
Ratio* (%)	1.91%	0.59%	0.51%	0.93%
High Target Volume				
In Treatment Units	4,021	1,843	1,492	2,754
Adjacent to Treatment Units	3,817	1,468	1,288	2,182
Outside Treatment Units	344,751	349,016	351,680	348,922
Total fire grid cells	352,589	352,327	354,460	353,858
Ratio * (%)	2.22%	0.94%	0.78%	1.39%

* Ratio of grid cells affected by treatments over total fire grid cells

CHAPTER 4

EFFECTS OF SPATIAL PATTERNS OF FUEL MANAGEMENT TREATMENTS ON HYPOTHETICAL HUMAN-CAUSED WILDFIRES

Kim, Young-Hwan

(To be submitted to *Forest Ecology and Management*)

4.1 ABSTRACT

In this research, we simulated wildfires that originated from hypothetical human-caused ignition points to determine whether a broad-scale schedule of fuel management treatments would be effective in reducing fire size or severity. The study area was a large watershed in northeastern Oregon. Fuel management treatments included commercial thinning, and thinning followed by prescribed fire. The fuel management treatments were distributed across the landscape in such a way as to simultaneously maximize both an even-flow of timber harvest volume and a spatial pattern of activity (dispersed, clumped, random, and regular). We found that the regular pattern of management activity seemed to reduce fire severity the most in 2 out of 3 cases. The dispersed pattern of management activity was scheduled for more area that was subsequently included in simulated fires, although the size and severity of fires was not reduced as much as in the regular pattern case. The clumped and random patterns of fuel management activities seemed to have no effect on simulated human-caused wildfires.

4.2 INTRODUCTION

Over the last few decades, managers and researchers have been investigating methods for reducing the risk of catastrophic wildfires in the western forests of North

America. Fuel reduction treatments have received interest recently as a primary fire management strategy, and have been extensively applied to this region. The beneficial effects of fuel treatment activities have been noted in many studies, but most were conducted at very local scales (Helms, 1979; Martin et al., 1989; Agee, 1998, Agee and Skinner, 2005, Stephens and Moghaddas, 2005). It has been suggested that a spatial distribution of fuel management activities on a landscape might efficiently disrupt the progress of wildfire (Shang et al., 2004; Agee and Skinner, 2005), and possibly be done in a cost-effective manner. This study focuses on determining whether fuel management activities, once implemented in a specific pattern on a large landscape, might reduce fire risk from fires that might logically be ignited by humans.

The concept of spatially distributing fuel management treatments across a landscape has been previously reported (Kim et al., submitted). In this work, it was shown that fuel management treatments, spatially allocated on a large landscape, reduced fire severity compared to control solutions (with no fuel management treatments), and that the efficiency of doing so was closely associated with overall intensity of treatments measured by the amount of harvested timber. However, this work assumed that fires were randomly distributed across the landscape. Here we are concerned with understanding whether spatial patterns of fuel management activities can effectively disrupt certain kinds of fires, those started by humans. In doing so, we assume that the ignition points of these fires are not random, and that they are located within short distances of major roads.

To enhance effectiveness of fuel management planning, it is necessary to understand the ignition type of wildfire – either natural-caused fire or human-caused fire – and ignition location where wildfires are most likely to occur. However, there is limited information available for one to understand potential ignition locations according to the ignition types. In the western U.S., wildfires primarily occur due to lightning strikes, thus it has been accepted that wildfires most likely occur at high-elevation areas.

However, recent studies have reported that ignition locations of naturally-caused fires were not necessarily related to elevation or frequency of lightning (Diaz-Avalos et al. 2001). Further, it was reported that the ignition of natural-caused fires was more likely influenced by weather conditions (Rorig and Ferguson 1999; Podur et al. 2003; Wotton and Martell 2005) or fuel conditions (Diaz-Avalos et al. 2001; Wotton and Martell 2005), rather than geological or topographical considerations. In addition, there is limited information about potential ignition location of human-caused wildfire (Wotton et al., 2003). However, through anecdotal information one could draw the conclusion that human-caused fires are often ignited near developed areas such as highways, recreation sites, or the wildland-urban interface. One could speculate that the effects of a spatial arrangement of fuel management treatments might be confounded given the various possible ignition locations. For example, if treatment activities were clustered around highways or campsites, these would seem to be most effective in disrupting human-caused wildfires, but not wildfires whose ignition points are randomly located. Therefore, by modeling ignition locations according to ignition type,

we expect to obtain practical results that will benefit fuel management or management planning efforts.

In this research, we modeled several sets of wildfire ignition locations that were assumed to be human-caused, and subsequently examined the effects of a spatial pattern of fuel management treatments on these simulated fires. Also, we adopted several management scenarios that were optimized for arranging fuel management treatments in spatial patterns across a large landscape in a recent research (Kim et al., submitted). The management scenarios have offered diverse treatment size, combination of treatment types, and treatment intensity. Therefore, in this research, three hypotheses are examined for comparison of management scenarios: 1) treatment effects on human-caused wildfires vary to treatment size, 2) the type of treatment activities influences the treatment effects on human-caused wildfires, and 3) treatment intensity differentiate the treatment effects on human-caused wildfires.

4.3 METHOD

In this section, we describe the study site in which this research was centered, the modeling process used in developing alternative scenarios, the methods for simulating wildfires, and how the simulation results were analyzed.

4.3.1 Study Site and Management Scenarios

The study site for this research is the Upper Grand Ronde River basin (approximately 178,000 hectares, Figure 4.1) located in northeastern Oregon, U.S., most of which is managed by the USDA Forest Service (Wallowa-Whitman National Forest), but small parcels of private forestlands are also included in the basin. Geographic and forest structure databases were provided by the Interior Northwest Landscape Analysis System project (La Grande Forestry and Range Science Lab, 2003), and included geographic information systems databases describing the vegetation (management units), roads, streams, and topography of the area, as well as tree lists pertaining to each management unit that were input into a growth and yield simulator to project forest conditions into the future (Bettinger et al., 2005).

In Kim et al. (submitted), a forest scheduling model based on a heuristic algorithm was developed to optimize an even-flow of timber harvesting volume (10,000 MBF) and four spatial patterns of fuel management treatments (dispersed, clumped, random, and regular pattern) for the same study site. Using the scheduling model, we were able to generate management scenarios that achieved an even-flow harvest volume target (Table 4.1) that arranged treatments in four spatial patterns with various treatment sizes (Figure 4.2). The five management scenarios (4 scenarios for the spatial patterns and 1 control) used in the previous research were adopted for this research. Two types of fuel management treatment activities were used in the management scenarios: thinning of ladder fuels and thinning followed by prescribed burning. The heuristic scheduling model developed in Kim et al. (submitted) included rules for choosing

amongst the management activities, which included the need to not only generate timber volume, but also to create a spatial pattern of activities across the landscape.

4.3.2 Fire Growth Simulation

For fire simulations, we used a fire growth model, FARSITE (Finney 1998), which has been utilized in several research projects (van Wagtendonk, 1996; Stephens, 1998; Finney, 2001; Finney, 2003; Stratton, 2004). For each FARSITE simulation, spatial information on topography and fuel conditions was required as an input in an ASCII raster file format. The required databases (elevation, slope, and aspect) were prepared using geographic information systems (GIS) software. The required forest structure GIS databases of fuel conditions (fuel type, canopy cover, stand height, and crown base height) were prepared for each management scenario, since fuel conditions could be influenced by management activities. Kim et al. (submitted) generated such inputs using their scheduling model, which was designed to automate the GIS data preparation of fuel conditions, thus these procedures were used here as well. Along with spatial information of topography and fuels, FARSITE also requires a set of assumptions regarding the weather conditions. A sample set of weather conditions (temperature, humidity, wind, and moisture) for a hypothetical extreme fire season in eastern Oregon was utilized for these wildfire simulations.

FARSITE provides several types of outputs describing a simulated fire and its simulated behavior. However, we primarily used fireline intensity and flame length for comparison of the fuel management treatment effects. To compare the fuel management

treatment effects according for the spatial pattern of activities that were scheduled, three sets of five ignition points were used to simulate fires that began along the main roads in the Upper Grande Ronde River basin. These ignition points were located by the authors and represent hypothetical human-caused fires from sources that original along the main roads. Three different sets were developed to determine how much the results will vary based on spatial variability of both the scheduled fuel management treatments and the ignition points themselves. Average length and average fireline intensity were used in this analysis to assess the effectiveness of the fuel management treatments.

To specify ignition locations of these hypothetical human-caused fires, a buffer zone was generated 10 meters around highways passing through the study site, and then 5 ignition points were selected randomly within the buffer zone. These 5 ignition points were considered as hypothetical ignition locations of human-caused wildfires, and applied consistently to all management scenarios (i.e., the same 5 ignition points were used in the fire simulation for the four patterns and the control solution). Two other sets of hypothetical ignition locations were also developed, thus wildfire simulations (5 management scenarios × 3 sets of ignitions) were developed for this analysis.

4.3.3 Analysis of Simulated Outputs

Output files resulted from FARSITE are composed of 30×30 meter grid cells, and each grid cells contains a value related to the simulated wildfires (flame length or fireline intensity). From grid cells burned by simulated fires, average, minimum, and maximum values of flame length or fireline intensity were calculated and compared to

specify the treatment effects of management scenarios. In addition, fire grid cells in each FARSITE output file were categorized into fire behavior classes, introduced by Rothermel and Rinehart (1983). Rothermel and Rinehart (1983) classified fire behavior, such as flame length and fireline intensity, into four severity classes and provided interpretation of fire behavior for each behavior class (Table 4.2). The interpretation was developed for the purpose of fire suppression, but it also provided a good interpretation of fire behavior and severity. Among the four behavior classes, class 3 and 4 are the classes in which fires were considered severe and not controllable by suppression efforts. In this research, fuel treatment activities were assumed to be able to reduce the areas where fire behavior might be classified as severe as proposed by Rothermel and Rinehart (1983). Thus, the number of fire grid cells were counted and summarized by the fire behavior classes for the comparison of treatment effects.

To enrich the analysis of the fire simulation outputs, the GIS data from FARSITE outputs again were categorized into three groups: grid cells in treatment units, grid cells adjacent to treatment units, and grid cells outside treatment units. This categorization was intended to help us understand whether overall treatment effects would vary by treatment size or not (testing hypothesis 1). To investigate the effect of fuel management treatment type, the number of fire grid cells affected by fuel treatment activities was summed. These results were utilized to test the hypothesis 2, that the type of fuel treatment activities influences the effects on human-caused wildfires.

In this research, treatment intensity was explained by the amount of merchantable timber harvest volume scheduled from the resulting forest plans. Thus, we

calculated how much volume was scheduled for harvest from the grid cells that were assumed burned in each FARSITE simulation, to examine whether treatment intensity actually had an effect on disrupting the hypothetical human-caused wildfires (hypothesis 3).

4.4 RESULTS AND DISCUSSION

The simulated fires are depicted in figure 4.3, 4.4, and 4.5, and the results of simulated outputs are summarized in tables 4.3 and 4.4. As one can see in table 4.3, neither flame length nor fireline intensity were effectively reduced by the spatial arrangement of fuel management activities using ignition set 1. Slight differences in simulated fire size, fireline intensity, and flame length can be seen, but one would conclude that the spatial patterns of fuel management activities did not effectively reduce simulated fire severity. Most of the management scenarios did not effectively influence the behavior of simulated fires using ignition set 2 either, however, the regular pattern significantly reduced flame length, fireline intensity, and fire size (Table 4.3), and decreased the number of fire grid cells in severe fire behavior classes (Table 4.4). In case of the ignition set 3, the regular pattern of activities was also effective, although the treatment effects were not as significant as those of ignition set 2 (Table 4.3). The total number of grid cells affected by fire using ignition set 2 and 3 was low when the clumped pattern of fuel management treatments was assessed (Table 4.3), however, the

area in the severe fire classes (classes 3 and 4) was lowest when the regular pattern of activities was assessed, adding to the mixed results (Table 4.4).

As mentioned earlier, treatment size was measured using the grid cells affected by fire, yet we also examined grid cells that were either located in or adjacent to management units where fuel management activities were scheduled. Table 4.5, 4.6, and 4.7 indicate that a larger percentage (3-4%, as compared to 1-2%) of the management units scheduled for treatment using a dispersed approach were either in, or adjacent to, fires. Also, a larger percentage of management units (1.6-1.9%) that were assumed to have been treated with a prescribed fire were also in, or adjacent to, fires. Since the total harvest volume over the entire planning horizon was higher in grid cells affected by fire when using the dispersed or regular patterns of fuel management activities (Table 4.8), one could assume that perhaps the spatial arrangement of harvesting was such that a larger portion of volume was extracted in areas that were subsequently affected by fire when using the dispersed or regular patterns of activities. The average volume extracted per unit area from treatment areas that were subsequently involved in a wildfire did not show a consistent pattern (e.g., it was high when using the clumped pattern). In addition, the difference between the clumped and random patterns and the others can be said to be influenced by the amount of prescribed burning that was scheduled (Table 4.5, 4.6, and 4.7). That is, lower amounts of prescribed fire were scheduled in areas that were subsequently affected by fire than when using the regular or dispersed spatial patterns of management treatments.

4.5 CONCLUSIONS

In this research, we examined whether a spatial arrangement of fuel management treatments would affect hypothetical human-caused wildfires. Flame length, fireline intensity, and fire size were measured on simulated fires to assess the severity of wildfires ignited in hypothetical human-caused locations. The resulted outputs of fire simulation supported the fact that human-caused wildfire could be disrupted by fuel management treatments, but the effectiveness of treatments could be influenced by treatment type and intensity applied.

While we found that the regular pattern of management activity seemed to reduce fire severity the most in 2 out of 3 cases, more case studies would enhance the notion that this pattern is more suitable for large-scale treatment distribution than other patterns of activities. Further, human-caused fires were assumed to occur along major roads. This hypothesis could be expanded to heavily-traveled trails or heavily-used recreational areas. While the main issue in fuel management treatments may be to cover the most area as possible, or the most highly fire-susceptible area as possible, organizational budgets may preclude this from happening. Therefore, a broad-scale arrangement of fuel management treatments in a spatial pattern has been proposed, and our work suggests that a regular pattern of activity, which both produces timber products and controls fuels, may be more effective at reducing fire size and severity than other patterns.

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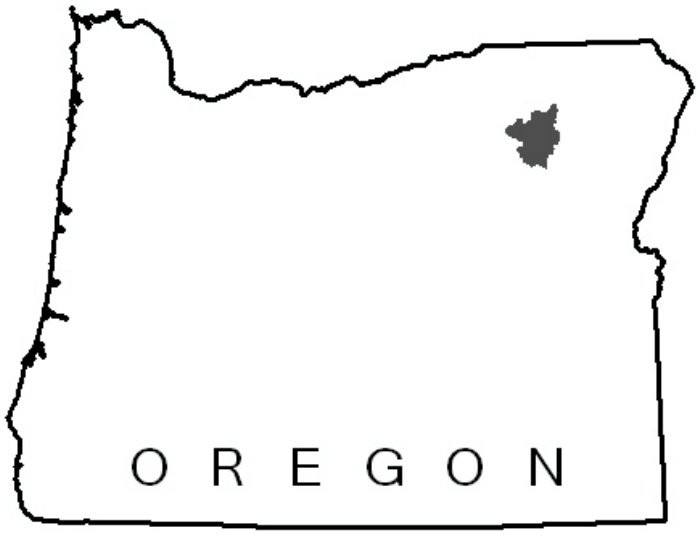

Figure 4.1 – Study site: Upper Grand Ronde River basin in northeastern Oregon (USA)

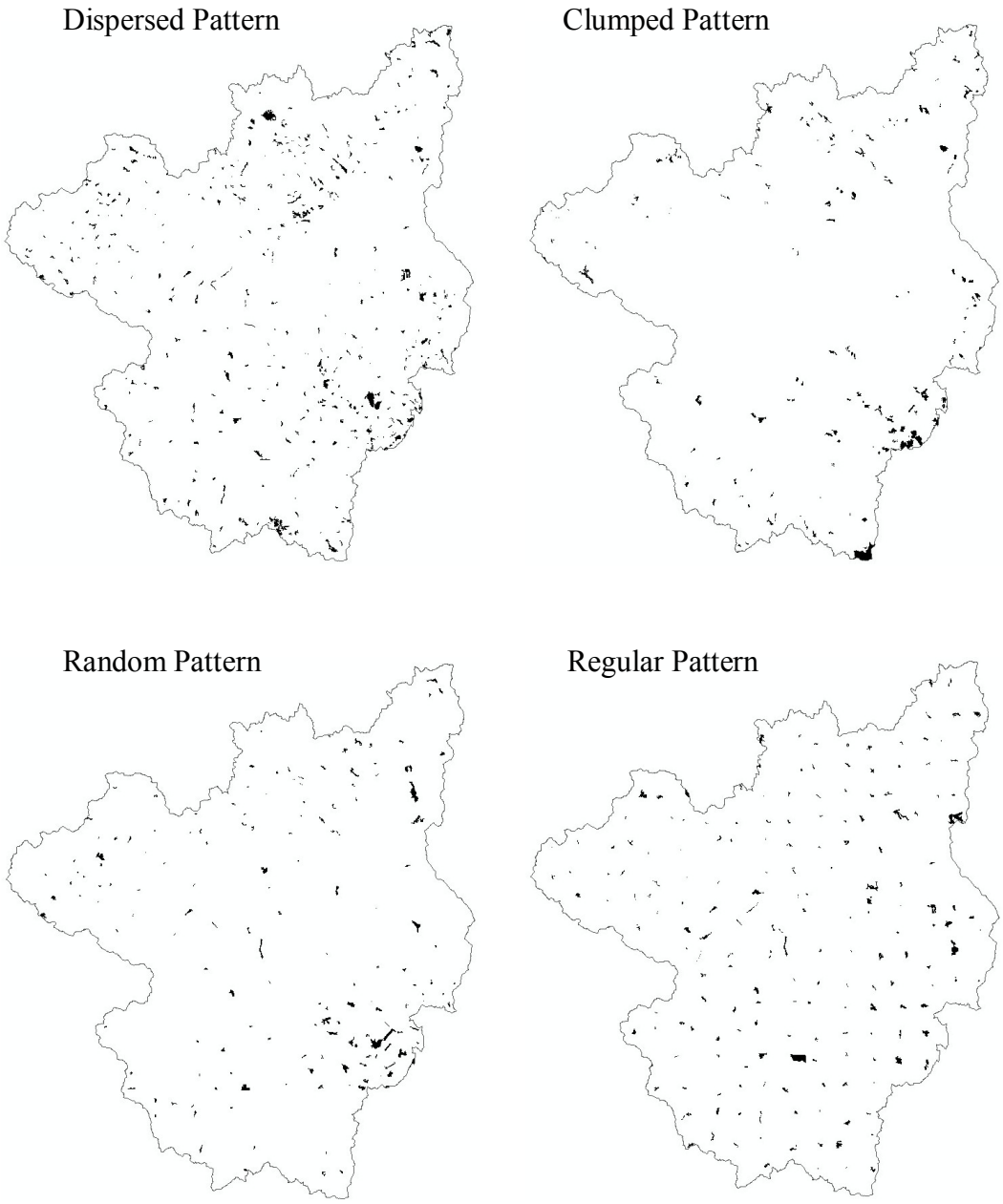

Figure 4.2 – Optimized spatial patterns of treatment units

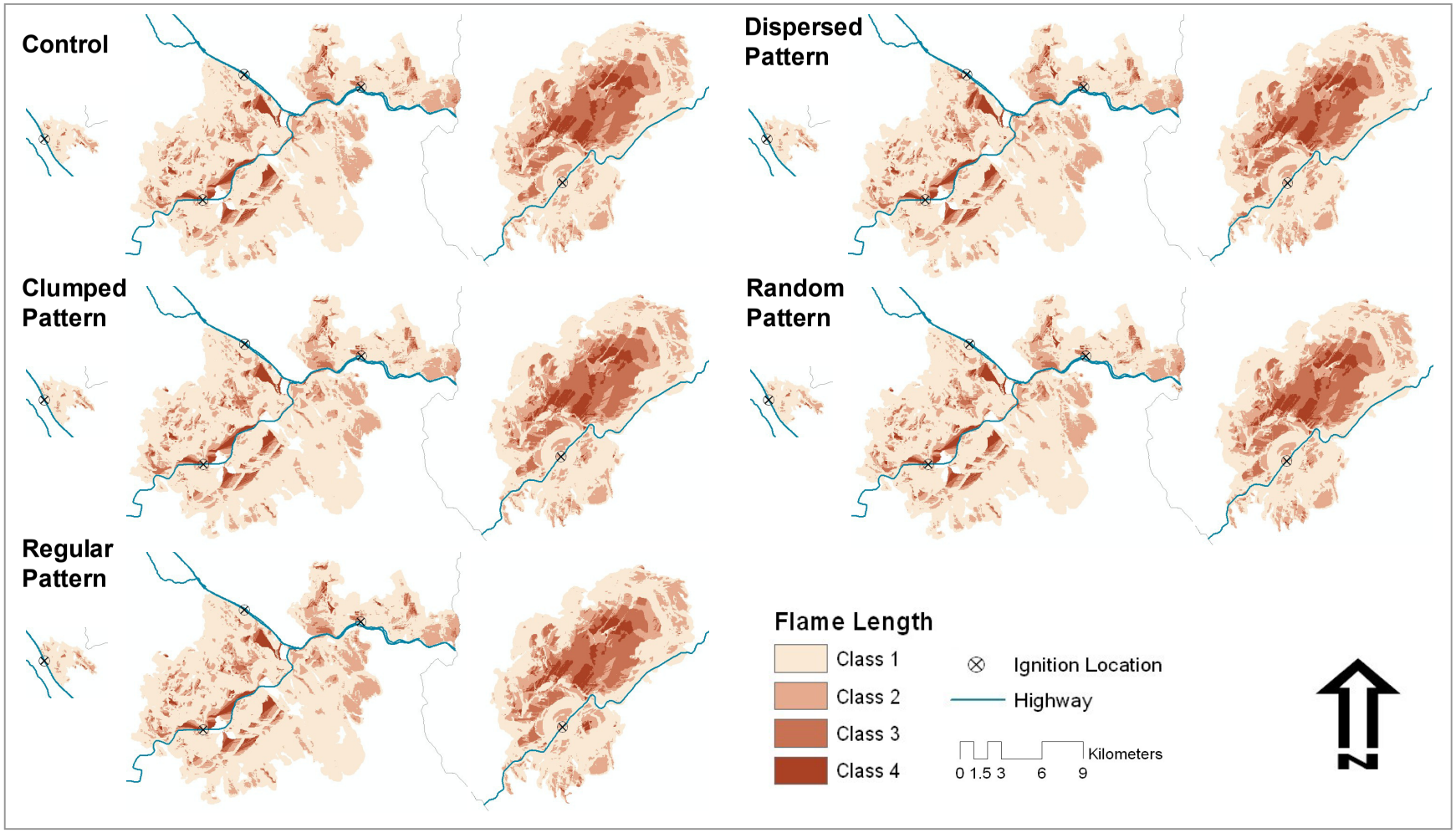

Figure 4.3 – Results of fire simulation: flame length for ignition set 1

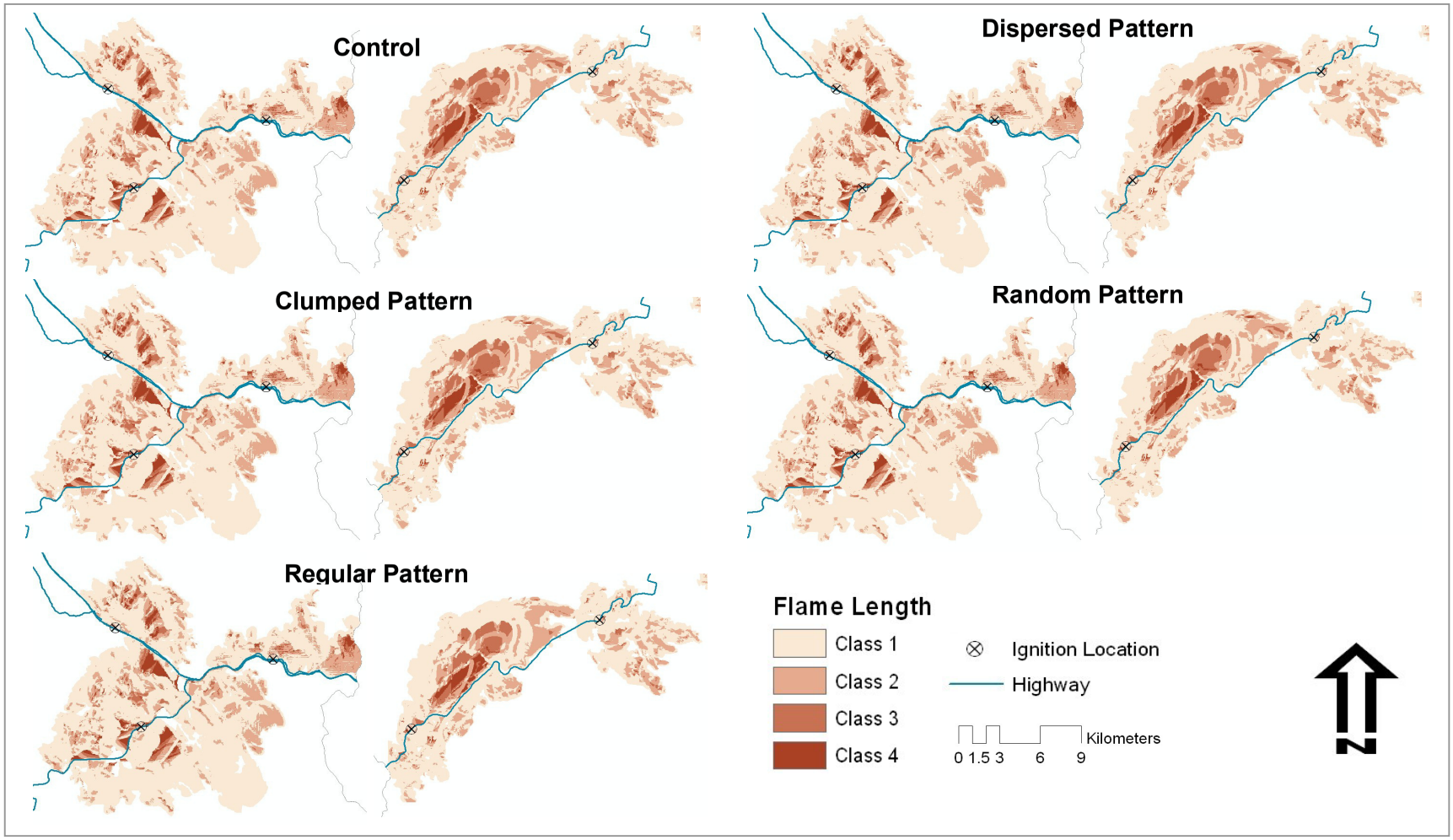

Figure 4.4 – Results of fire simulation: flame length for ignition set 2

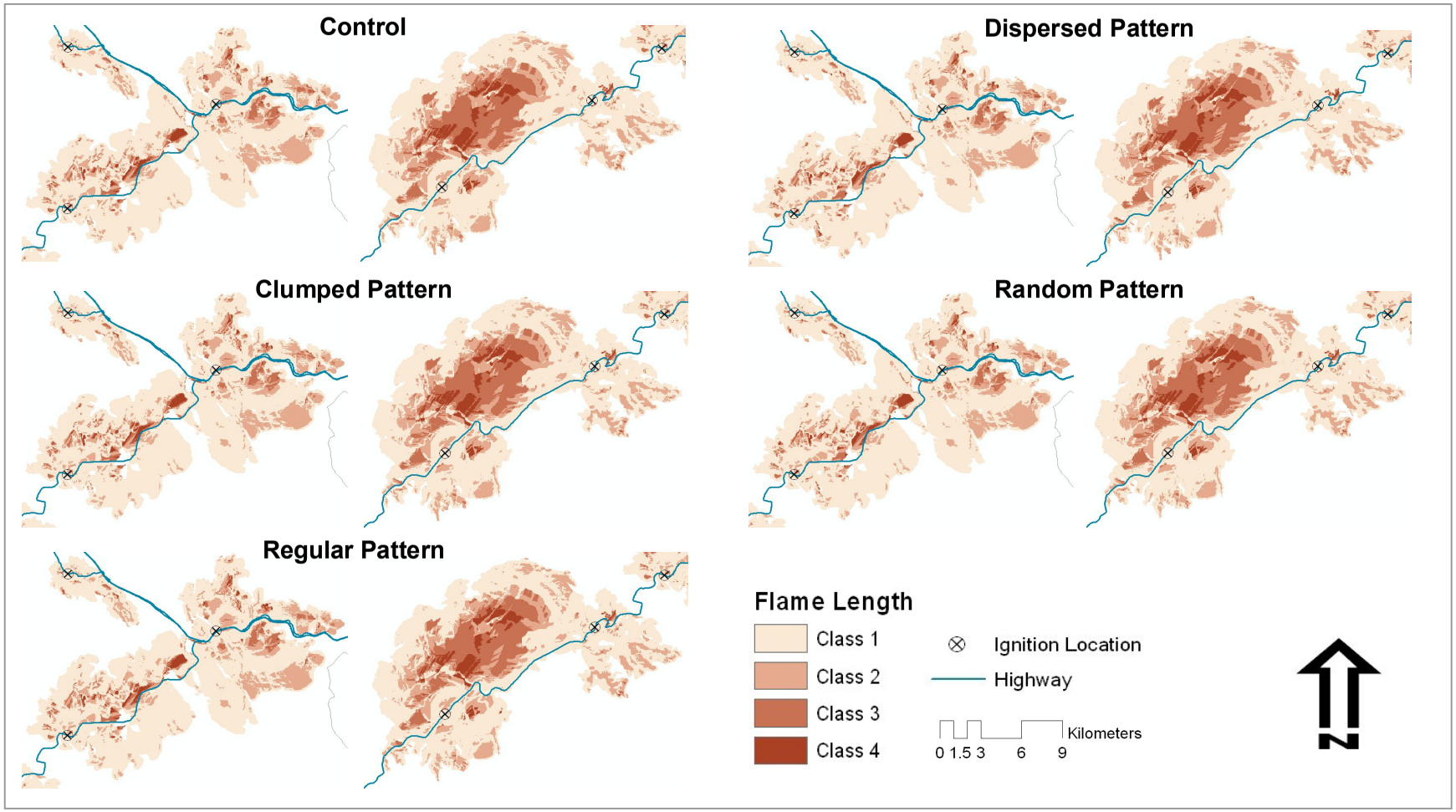

Figure 4.5 – Results of fire simulation: flame length for ignition set 3

Table 4.1 – Harvest volume (MBF) of the optimized solution for each spatial pattern

Management Period	Dispersed Pattern	Clumped Pattern	Random Pattern	Regular Pattern
Period 1	10,002	10,000	10,000	10,000
Period 2	10,004	10,000	10,000	-
Period 3	10,003	10,000	10,000	-
Period 4	10,002	10,000	10,000	-
Period 5	10,007	10,000	10,000	-
Period 6	10,003	10,000	10,000	-
Period 7	10,008	10,000	10,000	-
Period 8	10,010	10,000	10,000	-
Period 9	10,000	10,000	10,000	-
Period 10	10,002	10,000	10,000	-

Table 4.2 – Interpretation of Fire Behavior *

Classes	Flame Length	Fireline Intensity (Btu/ft/s)	Interpretations
1	< 1.2 m (< 4 ft)	< 100	Fires can generally be suppressed by persons using hand tools at the head or flanks
2	1.2 ~ 2.4 m (4 ~ 8 ft)	100 ~ 500	Fires are too intense for direct suppression on the head by persons using hand tools. Equipment or vehicles would be required for suppression, but effective.
3	2.4 ~ 3.4 m (8 ~ 11 ft)	500 ~ 1000	Fires may start torching out, crowning and spotting. Suppression at the fire head is probably ineffective to control fires.
4	3.4 m < (11 ft <)	1000 <	Crowning and spotting would be occurred. Suppression efforts at the fire head are ineffective.

* Source: Rothermel and Rinehart (1983)

Table 4.3 – Fire simulation results of the optimized solutions (in the fire time period)

Fire Behavior	Control	Dispersed Pattern	Clumped Pattern	Random Pattern	Regular Pattern
Ignition Set 1					
Flame Length (meter)	1.172	1.171	1.170	1.173	1.172
Change from control	-	(-0.001)	(-0.002)	(+0.001)	-
Fireline Intensity (Btu/ft/s)	195.002	195.324	194.846	195.509	194.994
Change from control	-	(+0.322)	(-0.157)	(+0.506)	(-0.009)
Fire Size (ha)	20,483	20,471	20,603	20,524	20,815
Change from control	-	(-12)	(+120)	(+41)	(+333)
Ignition Set 2					
Flame Length (meter)	1.047	1.049	1.050	1.046	1.033
Change from control	-	(+0.002)	(+0.003)	(-0.001)	(-0.014)
Fireline Intensity (Btu/ft/s)	151.823	153.036	153.323	152.263	148.397
Change from control	-	(+1.213)	(+1.500)	(+0.440)	(-3.426)
Fire Size (ha)	20,317	20,169	20,060	20,181	19,891
Change from control	-	(-148)	(-257)	(-136)	(-426)
Ignition Set 3					
Flame Length (meter)	1.130	1.128	1.136	1.130	1.129
Change from control	-	(-0.002)	(+0.006)	-	(-0.001)
Fireline Intensity (Btu/ft/s)	180.314	179.484	181.768	180.731	179.295
Change from control	-	(-0.830)	(+1.454)	(+0.417)	(-1.019)
Fire Size (ha)	19,741	19,756	19,486	19,838	19,575
Change from control	-	(+15)	(-255)	(+97)	(-166)

Table 4.4 – Fire simulation results by the fire behavior class: number of grid cells in each fire behavior classes

	Fire Behavior Classes		Control	Dispersed Pattern	Clumped Pattern	Random Pattern	Regular Pattern
Ignition Set 1	Flame Length	Class 1	153,714	153,094	154,526	153,735	155,444
		Class 2	44,940	45,200	45,254	45,017	46,524
		Class 3	20,979	21,322	21,187	21,347	21,269
		Class 4	7,950	7,831	7,948	7,943	8,041
	Fireline Intensity	Class 1	147,316	146,994	148,141	147,435	148,936
		Class 2	50,527	50,456	50,824	50,436	52,201
		Class 3	20,989	21,338	21,177	21,400	21,207
		Class 4	8,751	8,659	8,773	8,771	8,934
Ignition Set 2	Flame Length	Class 1	163,050	161,283	160,818	162,031	161,397
		Class 2	44,391	44,276	43,528	43,910	42,235
		Class 3	12,239	12,293	12,435	12,193	11,430
		Class 4	6,060	6,248	6,105	6,094	5,943
	Fireline Intensity	Class 1	156,339	154,725	154,157	155,419	154,851
		Class 2	50,477	50,177	49,585	49,864	48,267
		Class 3	12,159	12,253	12,272	12,155	11,225
		Class 4	6,765	6,945	6,872	6,790	6,662
Ignition Set 3	Flame Length	Class 1	149,666	149,851	147,376	150,500	148,551
		Class 2	43,457	43,578	42,984	43,698	43,063
		Class 3	19,984	19,978	19,904	19,971	19,894
		Class 4	6,233	6,098	6,244	6,250	5,991
	Fireline Intensity	Class 1	143,605	143,662	141,167	144,344	142,365
		Class 2	48,748	48,971	48,409	49,039	48,454
		Class 3	19,939	20,023	19,882	19,997	19,911
		Class 4	7,048	6,849	7,050	7,039	6,769

Table 4.5 – Number of fire grid cells affected by fuel treatments: Ignition Set 1

	Dispersed Pattern	Clumped Pattern	Random Pattern	Regular Pattern
Total fire grid cells	227,447	228,915	228,042	231,278
In Treatment Units	4,704	1,543	1,875	2,924
Thinning Only	2,171	810	1,464	1,615
Thinning & RX Burn	2,533	733	411	1,309
Adjacent to Treatment Units	3,550	978	1,072	2,099
Thinning Only	1,863	395	654	1,143
Thinning & RX Burn	1,687	583	418	956
Ratio of Overall Treatment*	3.63 %	1.10 %	1.29 %	2.17 %
Ratio of RX Burn**	1.86 %	0.57 %	0.36 %	0.98 %

* Ratio of grid cells affected by treatments (grid cell in treatment units or adjacent to treatment units) over total fire grid cells
** Ratio of grid cells affected by prescribed burning over total fire grid cells

Table 4.6 – Number of fire grid cells affected by fuel treatments: Ignition Set 2

	Dispersed Pattern	Clumped Pattern	Random Pattern	Regular Pattern
Total fire grid cells	224,100	222,886	224,228	221,005
In Treatment Units	5,060	2,293	1,919	2,933
Thinning Only	2,740	1,500	1,506	1,425
Thinning & RX Burn	2,320	793	413	1,508
Adjacent to Treatment Units	3,723	1,531	1,167	2,151
Thinning Only	2,076	857	766	956
Thinning & RX Burn	1,647	674	401	1,195
Ratio of Overall Treatment*	3.92 %	1.72 %	1.38 %	2.30 %
Ratio of RX Burn**	1.77 %	0.66 %	0.36 %	1.22 %

* Ratio of grid cells affected by treatments (grid cell in treatment units or adjacent to treatment units) over total fire grid cells
** Ratio of grid cells affected by prescribed burning over total fire grid cells

Table 4.7 – Number of fire grid cells affected by fuel treatments: Ignition Set 3

	Dispersed Pattern	Clumped Pattern	Random Pattern	Regular Pattern
Total fire grid cells	219,505	216,508	220,419	217,499
In Treatment Units	3,917	1,184	1,020	2,829
Thinning Only	1,900	688	522	1,492
Thinning & RX Burn	2,017	496	498	1,337
Adjacent to Treatment Units	3,350	810	1,001	2,075
Thinning Only	1,818	399	459	1,041
Thinning & RX Burn	1,532	411	542	1,034
Ratio of Overall Treatment*	3.31 %	0.92 %	0.92 %	2.25 %
Ratio of RX Burn**	1.62 %	0.42 %	0.47 %	1.09 %

* Ratio of grid cells affected by treatments (grid cell in treatment units or adjacent to treatment units) over total fire grid cells
** Ratio of grid cells affected by prescribed burning over total fire grid cells

Table 4.8 – Harvest volumes (board ft) from fire grid cells in treatment units

	Dispersed Pattern	Clumped Pattern	Random Pattern	Regular Pattern
Ignition Set 1				
Total Harvest Volume*	1,226,739	566,056	370,677	967,692
Average Volume**	261	367	198	331
Ignition Set 2				
Total Harvest Volume*	1,411,824	1,040,655	396,316	1,250,455
Average Volume**	279	454	207	426
Ignition Set 3				
Total Harvest Volume*	914,597	437,737	242,090	905,727
Average Volume**	233	370	237	320

*Total harvest volume from grid cells which is in treatment units
**Average harvest volume from each grid cell which is in treatment units

CHAPTER 5

GENERAL

CONCLUSIONS

In this research, I was able to develop a scheduling model that provided approaches in which fuel management activities were scheduled in four spatial patterns across a large landscape. The solutions optimized through the scheduling process presented variety of dispersion of activity as well as a variety of treatment sizes, but also evenly distributed the harvest volume through the multi-decade time horizon (Chapter 2 and 3).

The spatial patterns of scheduled activities are being represented fairly well through visual examinations, but a validation process of the patterning was also employed. By applying a nearest neighbor distance analysis, which is one of a set of point pattern analysis techniques, I was able to assess the spatial patterns in a statistical manner. From the statistical analysis, I found that the spatial patterns were not necessarily realized for some desired patterns, even though they were visually apparent (Chapter 2). However, by inserting a statistic related to the nearest neighbor distance analysis into the objective function of the scheduling model, I was able to develop a more advanced scheduling model which enables forest planners or managers to adopt the concept of spatial optimization in fuel management (Chapter 3).

To understand cumulative effects of fuel treatments on the wildfire behavior, several hypotheses were examined in this research. First of all, I examined whether the treatment size – the amount of overall scope of fuel management treatments – made any difference in the reduction in fire severity. To assess the impact of treatment size, two levels of harvest volume targets were applied in the scheduling process, where about 1% (low volume target) and 7% (high volume target) of the study sites were scheduled

for treatments. However, the results of fire simulation showed that fire severity is not effectively reduced if there is no specific control of critical fuels such as ladder or surface fuels, no matter of treatment size (Chapter 2).

In the subsequent study (Chapter 3), additional treatment prescriptions that were intended to control ladder fuels and surface fuels were applied: thinning ladder trees (from small-diameter range), and thinning followed by prescribed fires. Then, I tested the assumption that treatment effectiveness on fire behavior was either influenced by overall treatment size or applied treatment type. From the fire simulations, I found that fuel management treatments with the additional treatment prescriptions could possibly reduced fire severity when they were scheduled in the dispersed and regular patterns, and that treatment effectiveness did vary by treatment size (Chapter 3).

To enhance the effectiveness of fuel management planning, it was suggested that I also understand the ignition type of wildfires, and the potential ignition location where wildfires are most likely to occur. Although limited information was available to understand potential ignition locations of human-caused fire, I examined the effects of a spatial pattern of fuel management treatments on these types of fires. For this examination, it was necessary to make an assumption that human-caused fires are most likely to occur near developed areas such as highways, recreation sites, or the wildland-urban interface. Therefore, fires were simulated using several sets of ignition locations that were placed along the main road system, and then flame length, fireline intensity, and fire size were measured from the simulated fires. The resulting outputs of the fire simulation supported the notion that human-cause wildfire could be disrupted by fuel

management treatments that were spatially arranged in a regular pattern, one which provided higher proportion of prescribed fires and higher harvest volume per each unit area. This result supported the fact that the effectiveness of fuel management treatments would vary by treatment type and intensity applied (Chapter 4).

Through this research, I have learned that fuel management treatments could disrupt the progress of wildfires and alter fire behavior, but the effectiveness of treatments would vary to treatment size, type, and intensity. Among the four spatial patterns examined, the regular pattern seems to be the most acceptable pattern, since it provided the highest frequency in which simulated fires contacted the management units, and the highest treatment intensity measured by amount of harvested volume from a unit area.

In this research, however, several limitations were found; thus it was inevitable that I used a number of assumptions. For example, since modeling post-fire fuel conditions in individual stands was not available at this time, the management prescription of 'thinning followed by prescribed fire' was developed by modifying a thinning prescription with assumptions that prescribed fire would kill all trees less than 2 meter height and remove about 50% of surface fuel loads. Therefore, this research could be enhanced in the future by adopting more precise management prescriptions for post-fire fuel conditions. Also, it was necessary to develop several assumptions regarding to the ignition location of hypothetical human-caused wildfires, because limited information is available. Thus, in this research, the hypothetical ignition locations were selected from a buffer zone which was generated 10 meters around

major roads passing through the study site. A further study using expanded ignition locations (i.e., recreation areas, unauthorized camping sites) or hypothetical natural-caused ignition locations (other than random locations) could provide more practical and reliable findings for fuel management planning.

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APPENDIX

APPENDIX 1

SOURCE CODE OF SCHEDULING MODEL, ENFAST

(CD included)