Spatial Optimization of Fuel Management Activities

Young-Hwan Kim, Department of Forest Resources, Oregon State University, Corvallis, OR 97331. Phone: 541-737-3090. Fax: 541-737-3049. E-mail: young.kim@oregonstate.edu.

Pete Bettinger, Warnell School of Forest Resources, University of Georgia, Athens, GA 30602. Phone: 706-542-1187. Fax: 706-542-8356. E-mail: pbettinger@forestry.uga.edu.

Mark A. Finney, USDA Forest Service, Fire Sciences Laboratory, Rocky Mountain Research Station, PO Box 8089, Missoula, MT 59807. Phone: 406-329-4832, Email: mfinney@fs.fed.us

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Abstract

We describe and assess several methods for scheduling 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 is 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 describe forest planning scheduling processes that provide 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 indicate that while spatial patterns cannot be statistically validated, due to the multi-objective nature of the planning problem, usual examination does suggest the patterns are being designed. In addition, fire behavior, as compared to a control simulation with no scheduled activity, is not minimized by scheduling activities in specific spatial patterns. Two reasons for this result emerge: (1) that the prescriptions used, which were designed to promote the development of forest structure within a desired range of stand density, are 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 are not significantly influenced by scheduling them in a pattern across the landscape.

Key worlds: wildfire, simulation, forest planning, landscape pattern

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 and other, 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 behaviors.

Because of the difficulty of conducting experimental work at a large scale, and because of the unpredictability of wildfire, previous research regarding to 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 modeling 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 models, given the non-linear nature of the problem.

The overall objective of this study is to understand how spatial patterns of fuel management activities influences wildfire behavior. In this paper, we primarily describe and assess 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 fuel managements on wildfire behavior when applied to a larger watershed in eastern Oregon (USA).

Methods

Study Site and Data Preparation

In previously reported preliminary research (Kim and Bettinger, in press), scheduling methodologies for spatial arrangements of management activities were tested in private lands located within the Upper Grand Ronde River basin in northeastern Oregon. 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 hectare, Figure 1).

GIS databases representing the current forest structure of the watershed were downloaded from the website of the 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 generated. In addition, scheduling of fuel management activities requires 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.

In Bettinger et al. (in review), 10 stand-level optimal prescriptions were developed, each with the goal of maintaining desired stand density targets for each stand, while being limited by operational constraints. Changes in stand structure over 10 ten-year periods (100 years) were simulated. These 10 prescriptions and their associated data were adapted to this research. Bettinger et al. (in review) examine a simple economic goal – maximize even-flow of timber harvests – and how changes in heuristic processes affect the efficiency of forest plans. They do not model either wildfire behavior, or spatial patterns of activities.

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 Deuck (1993) and applied to forest planning problems in Bettinger et al. (2002), and Kim and Bettinger (in press).

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 review), a maximum even-flow harvest volume (200,716 MBF per decade) was optimized through linear programming with simplifying management assumptions, where no spatial constraints were considered and integer variables were not 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.

<u>Dispersed Pattern of Fuel Management Activities</u>

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 harvest to the target

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 : Index of management periods

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). 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 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 1.

Clumped Pattern of Fuel Management Activities

A clumped pattern is assumed to be a pattern in which management units are clustered on landscape. Here, the ideal clumped pattern is 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 is 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 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 are 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 equations 1, which corresponds to the dispersion of management units, is not necessary in the objective function. A few of the GDA parameters have been adjusted based on the trial runs of the scheduling model (Table 1).

Minimize

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

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 are 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 idea:

- 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 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 is 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 is intersected by any boundary vector surrounding the study site. That is to say, if a systematic point were 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 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 is 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 5):

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

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

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 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, in press), 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 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 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 following time period. By 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 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 is 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.

Point Pattern Analysis: Nearest Neighbor Distance

In the preliminary research (Kim and Bettinger, in press), 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, it was suspicious whether management activities have been scheduled in desired patterns. To provide confidence to the model, a reasonable criterion was requested with statistical test in assessing the scheduled patterns. Therefore, the nearest neighbor distance analysis, which is one 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, 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 the 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 clustered; if it was significantly larger, the pattern would be dispersed. The significant of difference between observed and expected mean was tested by using a z-statistic:

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

Where:

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

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

Fire Growth Simulation

To quantify changes in fire behavior resulted 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 wild fires. FARSITE requires spatial information on topography and fuels along with weather files as inputs, and such inputs should have grid file format. Thus, input files are generally prepared by using GIS software manually. To automate the data preparation, the scheduling model, originally developed in the preliminary research, was re-coded and combined itself with the original code of FARSITE. As the result, generating inputs associated with fuels and running FARSITE were available 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.

Results

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 7 and 8. According to the figures, the distinction between the spatial patterns can be visually verified when the low target volume applied (Figure 7), while distinction between patterns is more vague when using the high target volume (Figure 8). Because the private land within the study site consisted of a large area of meadow, management units in the private land were hardly selected for treatment.

The lack of treatment within the private land would be the primary reason for degrading the visual distinction between patterns.

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, most of resulting patterns were not verified as desired patterns (Table 2). While the regular pattern was accepted for both the low and high target volume, the dispersed pattern was not accepted for either case. The objective function utilized in the scheduling dispersed pattern intends to increase the total distance between the treatments. Although this tendency enabled a dispersed pattern to consist of a large number of management units, the increase of management units could not provide an acceptable level of significance when using the nearest neighbor distance.

Even Flow of Harvest Volume

As shown in the Table 3, the best solutions from the four spatial patterns produced 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 is due to the prescriptions available to the scheduling procedure and the scheduling procedure itself. There are 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 tends 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.

Fire Simulation

The results of fire simulation were summarized in the Table 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) and almost five times the area (Table 5), as compared to those optimized for the low volume target. As described in the Table 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.

Discussion

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 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 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 thinnings. 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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Table 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 – Results of point pattern analysis for scheduled patterns 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 (meter)	1417.75	2641.98	2552.81	3803.56
Expected Mean (meter)	1430.04	2821.52	2346.04	2250.80
z-statistic	-0.2428	-0.9110	1.5176	12.3815
Qualification	Reject	Reject	Accept	Accept
High Target Volume				
# of Units	967	456	614	476
Observed Mean (meter)	602.94	871.05	753.31	1150.15
Expected Mean (meter)	678.99	988.77	852.11	967.77
z-statistic	-6.6639	-4.8641	-5.4965	7.8661
Qualification	Reject	Accept	Reject	Accept

Table 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 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 (meter)	1.02 -	1.02 (0)	1.02 (0)	1.02 (0)	1.01 (-0.01)
Fireline Intensity (Btu/ft/s)	427.77	429.53 (+1.77)	427.89 (+0.12)	428.48 (+0.71)	419.66 (-8.10)
Fire Size (ha)	19328 -	19312 (-16)	19328 (0)	19306 (-22)	20930 (1602)
High Target Volume					
Flame Length (meter)	1.02 -	1.03 (+0.01)	1.02 (0)	1.02 (0)	1.03 (+0.01)
Fireline Intensity (Btu/ft/s)	427.77	435.81 (+8.04)	430.04 (+2.27)	434.14 (+6.37)	434.82 (+7.05)
Fire Size (ha)	19328 -	18871 (-457)	19141 (-187)	19128 (-200)	18799 (-529)

Table 5 – Treatment size (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%)

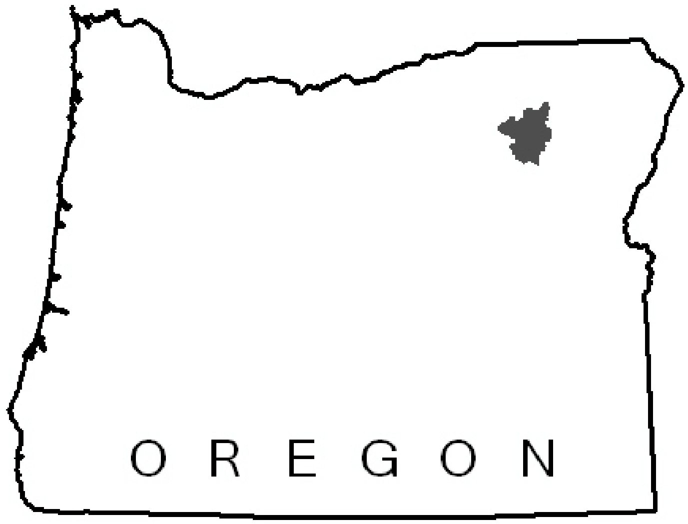

Figure 1. Study site: Upper Grand Ronde river basin in eastern Oregon.

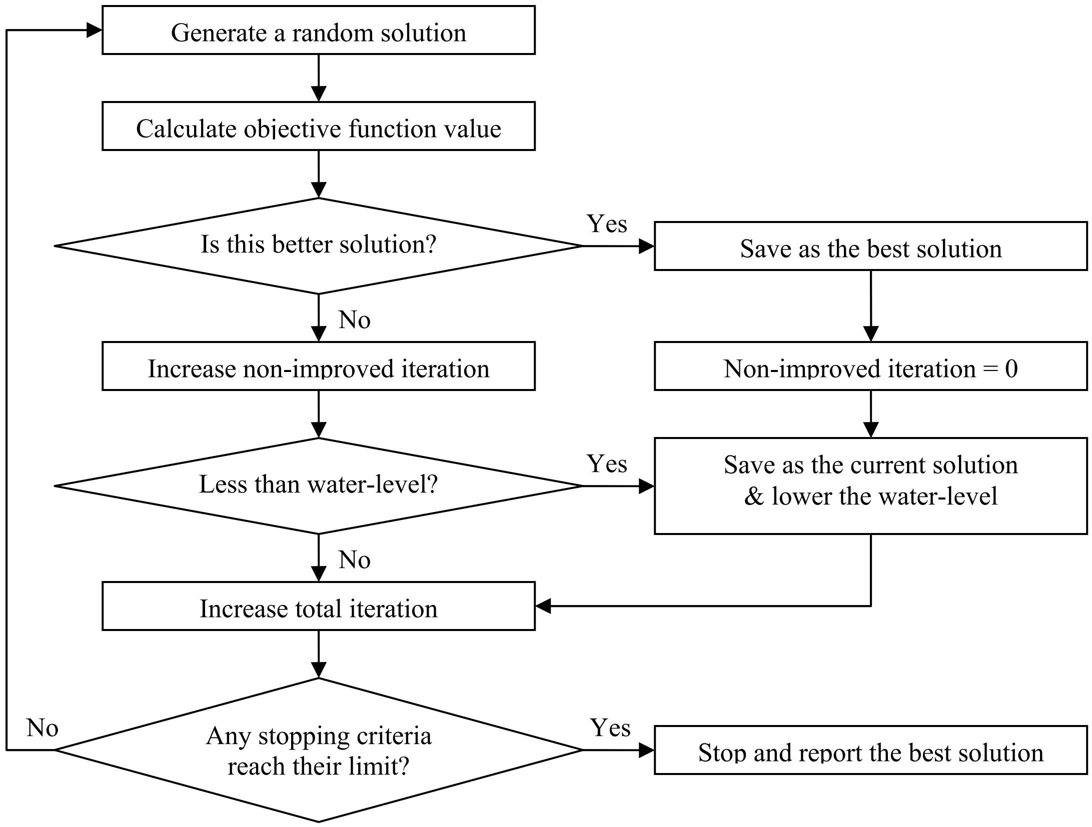

Figure 2. Flowchart of scheduling processes for dispersed, clumped, and random landscape pattern.

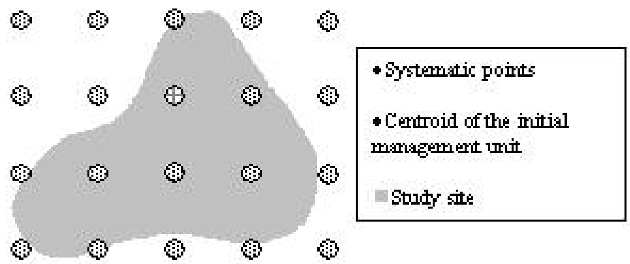

Figure 3. Systematic points generated to facilitate modeling the regular pattern.

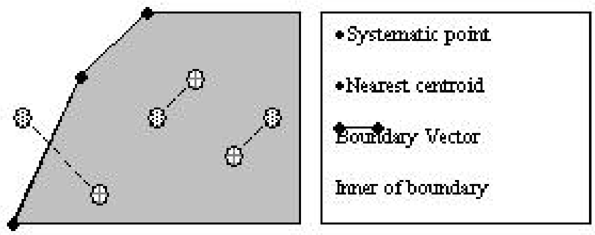

Figure 4. Vectors between systematic points and their nearest unit centroids.

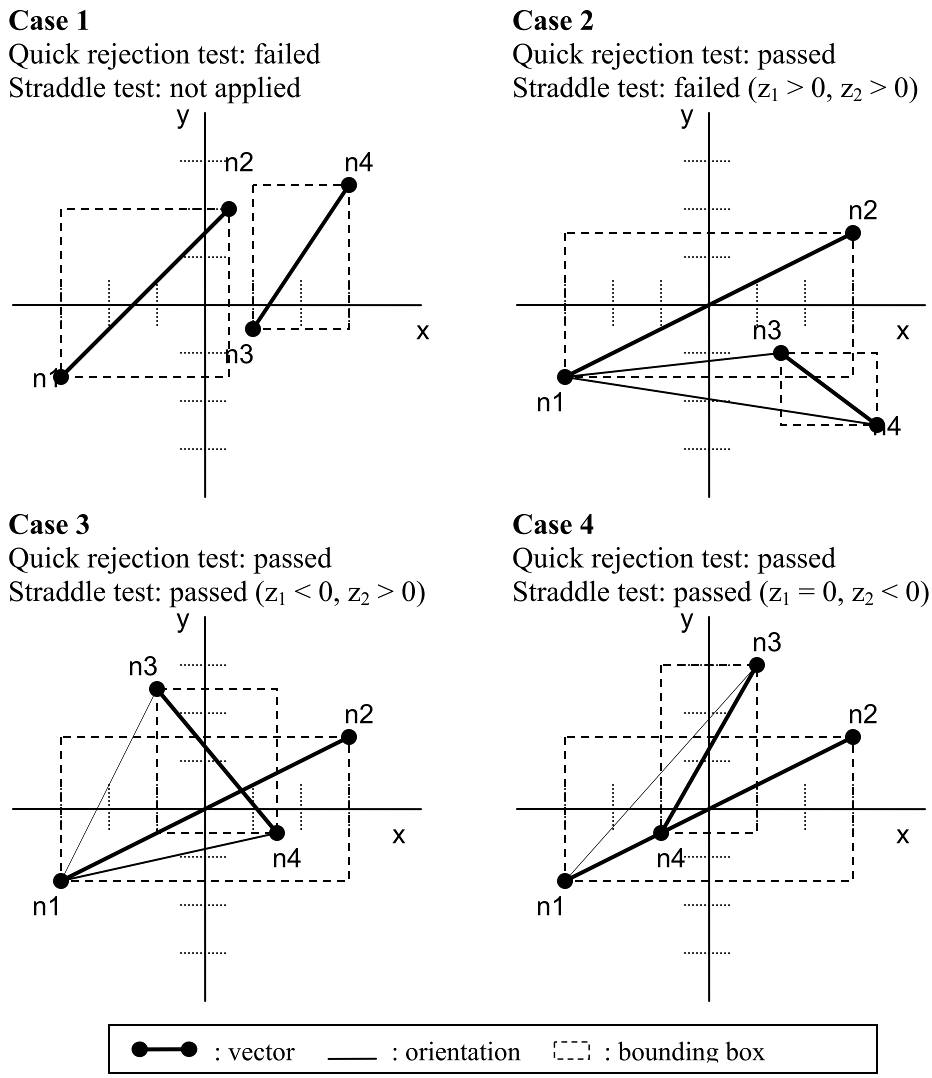

Figure 5. Examples of the quick rejection test and the straddle test for use in the generation of the regular landscape pattern.

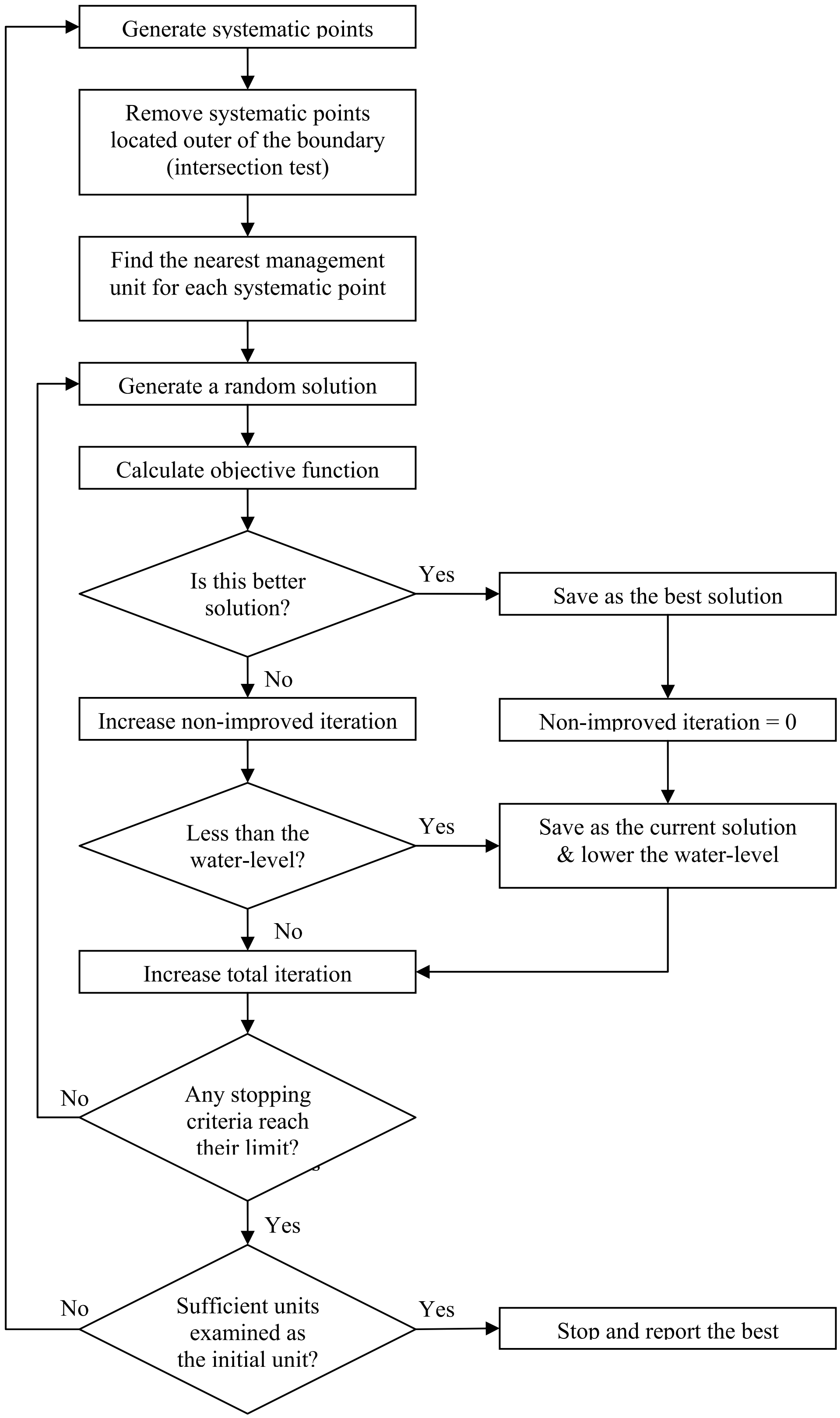

Figure 6. Flowchart of scheduling process for the regular pattern.

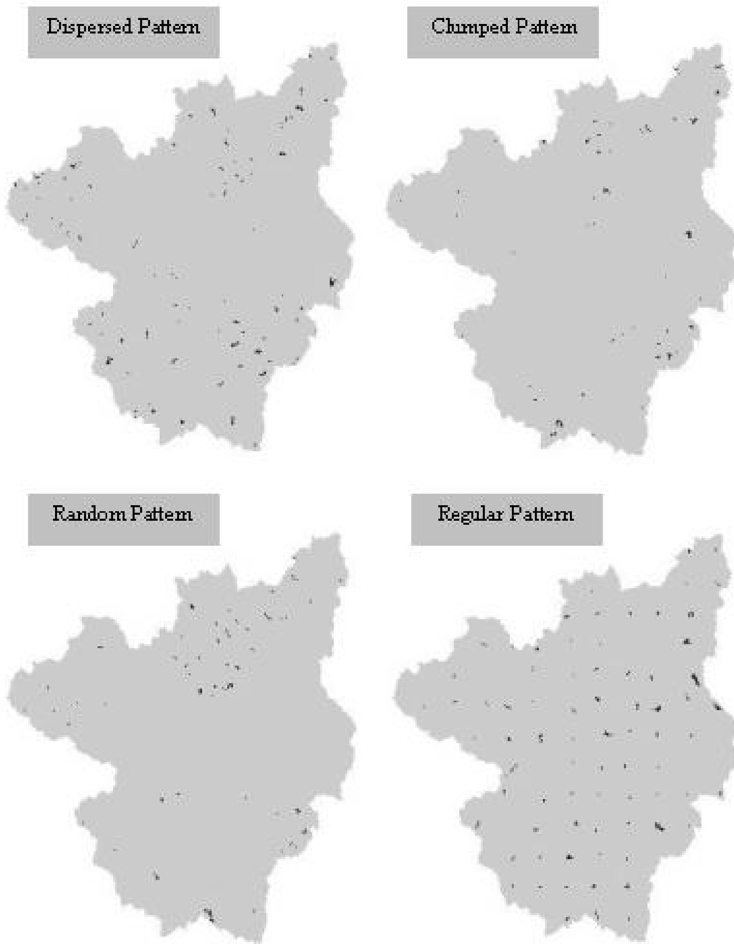

Figure 7. Spatial patterns of management units generated for the low target volume.

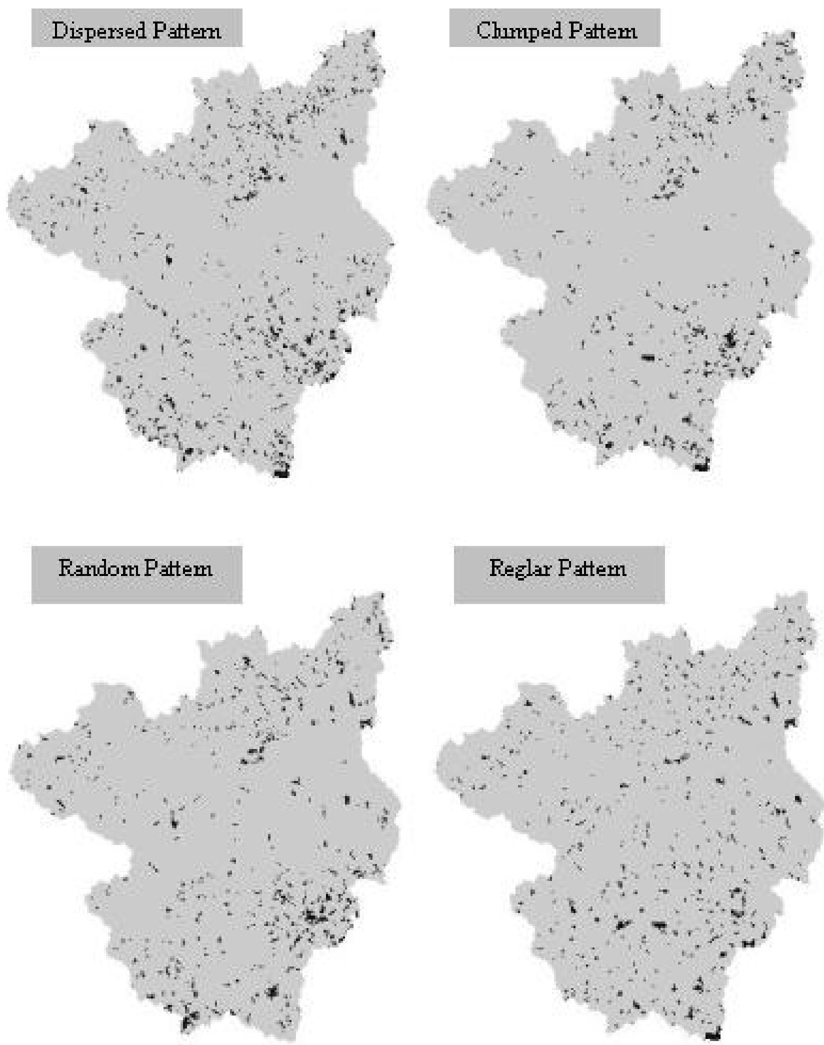

Figure 8. Spatial patterns of management units generated for the high target volume