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Spatial optimization of the pattern of fuel management activities and subsequent effects on simulated wildfires

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ABSTRACT

Methods for scheduling forest management activities in a spatial pattern (dispersed, clumped, random, and regular) are presented, with the intent to examine the effects of placement of activities on resulting simulated wildfire behavior. Both operational and fuel reduction management prescriptions are examined, and a heuristic was employed to schedule the activities. The main hypothesis is that simulated wildfire effects during a severe fire season may be mitigated by scheduling activities in a pattern across the landscape. Results suggest: (1) operational management prescriptions, designed to promote the development of forest structure within a desired range of stand density, were not appropriate for mitigating wildfire effects, and (2) increased harvest levels obscure spatial patterns of activity, making patterns less clear as harvests increase. Results also suggest that fuel reduction management prescriptions may marginally minimize wildfire severity during a severe fire season, when scheduled in a spatial pattern.

1. Introduction

Many western North American forests are threatened with high risk of a catastrophic wildfire. To reduce the consequences of catastrophic wildfires (i.e., cost of suppression, size of wildfires, 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 wildfire behavior on a local scale (Helms, 1979; Martin et al., 1989; Agee, 1998), but alone, may have limited influence on the overall behavior of wildfires across a large landscape. For example, isolated small fuels management units had negligible effect on the growth and progress of large wildfires in California chaparral in spite of the reduction of fire spread within the units (Dunn, 1989). However, it would be virtually impossible to treat entire forestlands in this region, given that they are so extensive, thus management activities need to be scaled and arranged in ways to effectively disrupt the behavior of wildfires.

Because of the difficulty in 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. Observations of wildland fire growth and behavior among forests of the Sierra Nevada (USA) support the idea that spatial fragmentation of fuels can cumulatively change wildfire size and behavior (van Wagtendonk, 1995; Parsons and van Wagtendonk, 1996). A critical factor, however, is the arrangement, size, and number of fuels management activities across landscape. 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 (USDA Forest Service, 2000) and the Sierra Nevada (USDA Forest Service, 2001). The fundamental difference between these two strategies is the role of individual management units. Fuel breaks are intended to reinforce defensible locations and thereby reduce wildfire 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 larger landscape pattern to reduce spread rate and intensity (Finney, 2001, 2003). With respect to protecting a wildland–urban interface, dispersed management treatments should slow the progress of wildfire towards the interface, while fuel breaks provide defensible space for crews immediately adjacent to developed areas.

The effectiveness of patterns of fuel management activities has been previously examined through small-scale studies. Random patterns of fuel management activities (Finney, 2003) have been

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shown to reduce spread rate in a sigmoid fashion, meaning that relatively large proportions of the landscape must be treated to substantially reduce fire sizes. Parallel strips (Fujioka, 1985; Martin, 1988; Catchpole et al., 1989) have been shown to be efficient at reducing fire spread rates (producing a harmonic mean spread rate) when small fractions of the landscape are treated. However, this strategy unrealistically requires the wildfire to move perpendicularly to the arrangement of strips. Regular patterns of dispersed fuel management activities (Finney, 2001) have been shown to reduce fire spread rate in a similar fashion to parallel strips, but the pattern is more flexible in accommodating other spatial management constraints.

A number of landscape simulation approaches have been used for spatially modeling wildfire and subsequent forest development (Keane et al., 1997; Jones and Chew, 1999; Mladenoff and He, 1999). Some of them have been proposed for modeling the effects of management and for optimizing the scheduling of fuel management activities. However, none of them account for the topological effects of fuel management patterns on landscape-scale wildfire behavior. Linear programming techniques are limited in their ability to achieve this requirement due to the absence of space and time controls on management scheduling, as well as its limits on modeling stochastic, complex disturbance processes. Therefore, heuristics and other integer programming methods are preferred for scheduling activities with spatial management goals. In addition, to model spatially variable wildfire effects at a fine-scale resolution, landscape units should be represented as either grid cells (raster data structure) or small polygons (Finney, 1999).

The methodology used in the Sierra Nevada Ecosystem Project, where effects of fuel breaks were modeled in the context of wildfire occurrence and forest change (Sessions et al., 1999), is one exception. This process utilized a spatially explicit simulation/optimization tool that featured a forest stand dynamics model, a stand management optimizer for dynamically selecting prescriptions at run time (not-prescheduled), a spatially explicit wildfire growth model, FARSITE (Finney, 1998), and a landscape optimization heuristic. The process allowed 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. However, the process did not allow one to develop a spatial pattern of fuel management activities, and to complicate matters, the modeling system (the integration of the four parts) is no longer in development nor supported by the original researchers. However, one part of the system continues to be supported and is widely used throughout North America (FARSITE).

In this research, we developed a modeling process that schedules management activities in a pattern across the landscape, then applied simulated wildfires to the landscape to determine whether the pattern of activity (and subsequent changes in fuels and forest structure) mitigates wildfire behavior. Two general hypotheses are considered: (1) management activities that are scaled and arranged in spatial patterns are effective in mitigating landscape-scale simulated wildfire behavior, and (2) cumulative effects of individual management activities on simulated landscape-scale wildfire behavior will be different according to the spatial pattern considered. Stand-level management plans are the basis of decisions in many natural resource management organizations (Rose et al., 1995) although a larger landscape-level plan accommodates broader goals that cannot be recognized at the stand-level. In either case, stands are the basic planning units. Spatial patterns of activities have been incorporated into planning frameworks at the landscape level. A number of papers have been published in the last 10 years illustrating how spatial patterns of activities, for example, can influence the maintenance of wildlife habitat (Bettinger et al., 2003). However, in the area of forest fuels management, work directed toward modeling optimal patterns of spatial activities, and a subsequent assessment of their efficacy for influencing fire behavior, is limited. Finney et al. (2006) provided one of the few examples, where pre-defined vegetative strips were created that would be treated with fuels activities, then the timing of those activities was optimized. As a result, we feel our contribution to the body of operational research sciences is in the integration of spatial patterns of scheduled activities into a planning framework, when scheduled at the stand-level, and the subsequent coordination of fire simulations with forest harvest scheduling techniques. Thus far, no other research has attempted these at the landscape-scale. Further, we address an important management consideration: can fuels reduction treatments that are arranged in a spatial pattern (due to budgetary restrictions) affect the spread of wildfires during a severe fire season.

2. Methods

2.1. Forest management modeling

In previously reported preliminary research (Kim and Bettinger, 2005), scheduling methodologies for spatial arrangements of management activities were tested in a small area of the Upper Grand Ronde River Basin. In this expanded research, refined methodologies of scheduling management activities in spatial patterns were applied to the larger watershed. In addition, we include here an analysis of effects of these patterns on simulated wildfire behavior, which was not included in the previously reported research. The four spatial patterns of fuel management activities we examined in this research includes three basic landscape patterns (dispersed, clustered, and random), and an artificial pattern (regularly spaced treatments). These spatial patterns of fuel management activities were scheduled using a single heuristic modeling technique, the Great Deluge Algorithm (GDA). GDA was introduced by Dueck (1993), applied to forest planning problems in Bettinger et al. (2002) and Kim and Bettinger (2005), yet has not previously been applied to forestry problems of this size. The great deluge algorithm was chosen based on three facts: (1) it is a fast heuristic, with a processing speed comparable to simulated annealing or threshold accepting, (2) it was used previously for a fuels management analysis in the Applegate watershed in Oregon (Graetz, 2000), and (3) the quality of results when applied to complex forest planning problems is as good as simulated annealing or threshold accepting (see Bettinger et al., 2002).

The amount of fuel management treatments applied on a landscape can be important in potentially altering wildfire behavior. If the treatment amount is too small, there may be little associated management effect because wildfires might have limited contact with treated management units. If the treatment amount is large, however, the spatial pattern of treatments may be lost. In a report by the US Government Accountability Office (2003), it was suggested that mitigating the risk of wildfires with fuels reduction treatments will require a long-term, sustained effort. Local land management offices prioritize land for treatment because funds are limited. Further, budgeted resources can be diverted from fuels management to other efforts, such as fire suppression. In addition, other factors such as administrative regulatory requirements and public resistance can limit the scope of fuels management efforts. To further complicate the problem, the allocation of funds from the national level to the local level is influenced by historical funding levels, and allocations tend to be proportionally similar year to year. Consequently, it is left to the local offices to identify the highest priority locations for fuels reduction treatments, and because of these factors, local offices fund fuels management on a case by case basis (US Government Accountability Office, 2003).

Since it is doubtful that an extensive fuel reduction treatment program will be feasible, we assume here that land managers may obtain the most benefit from limited budgets by spreading treatments across the broader landscape. In Bettinger et al. (2007), a maximum even-flow harvest volume was determined for the study site (1,137,557 m^3 per decade) using linear programming, simplifying management assumptions (i.e., no spatial constraints were considered and continuous variables were used to represent choices assigned to management units), and operational management prescriptions. Since we are assuming the resulting extensive harvesting program is not practical, two lower desired harvest levels are initially considered – one about 50% of the potential maximum harvest level (high volume target), and the other about 5% of the maximum (low volume target). The initial simulations, as we will see, use the operational management prescriptions. Based on what was learned with these simulations, the lower harvest levels are used when we employ the fuels reduction management prescriptions.

Scheduling procedures were repeated 30 times for each desired pattern of activities across the landscape to find the solution that best provides the desired pattern across landscape and best achieves the even-flow volume level. For quantifying the effects of patterns on simulated wildfire behavior, a control solution with no management activities scheduled was also generated.

2.1.1. Dispersed pattern of fuel management activities

In a dispersed pattern, treated areas are widely spread across the landscape with a minimum of clustering. Here, ideal dispersed patterns are assumed to maximize total distance between management units. Since an even-flow harvest volume is a desired outcome as well, the following objective function was developed to generate a pattern as close to the ideal pattern

$$\text{Minimize} \quad WH\sum_{t=1}^{T}\left(\left|\left(\sum_{i\in N_t} H_{it}\right) - TV_t\right|\right) - WD \times \sum_{t=1}^{T}\left(\sum_{i\in N_t - 1}\sum_{j\in N_t} D_{ij}\right), \tag{1}$$

where

WH = weight corresponding to the even-flow harvest volume objective,
WD = weight corresponding to the dispersion objective ($WH + WD = 1$),
H_{it} = harvest volume from unit i in time period t,
TV_t = target timber harvest volume for time period t,
D_{ij} = distance between centroids of unit i and j,
i, j = index of management units scheduled for harvest,
t = a time period,
T = total number of time periods ($T = 10$),
N_t = the set of management units scheduled for harvest in time period t.

The formulation we use represents a bicriteria optimization model. Another approach would have been to recognize one objective, and use the other concern as a hard constraint, however both concerns (harvest volume and spatial pattern) were deemed equally important. The set N_t is determined by the optimization model during the development of a forest plan, and is continuously changed and updated as management units are scheduled for treatment. The target volume (TV_t) is constant for each decade and constant across the time horizon. Other methods could have been used to vary the target volume, however we use a constant amount here to represent the achievement of the commodity production goal. The harvest volume from each management unit (H_{it}) is a function of the management prescription applied to the stand. The value associated with H_{it} is constrained in the sense that they could range from 0 volume units (no harvest) to the total volume within the management unit during the time period under consideration (t). However, since the management prescriptions preclude the use of a clearcutting option, the latter case is not possible. The H_{it} values are small compared to the target volume (TV_t) for the entire landscape, therefore a number of management units (i) need to be scheduled for harvest for the sum of H_{it} values to approach the target volume (TV_t). The sum of the H_{it} values are not constrained, however, and could range below and beyond the target volume (TV_t).

The scheduling procedure seeks a solution that minimizes the difference between actual harvest volume and a target harvest volume, and maximizes the total distance between centroids of management units scheduled for harvest. The GDA algorithm begins with a randomly defined feasible solution, and thereafter (Fig. 1) is considered a 1-opt solution generation process, where the status of a single management unit is altered randomly in an attempt to improve the quality of a forest plan. Each alteration to a forest plan results in a feasible solution, therefore no penalty functions are used to force the process to return to the feasible region of the solution space. Since we are minimizing an objective function value, GDA allows non-improving changes to be made to a solution as long as the change results in an objective function value that is not too far away from the best objective function value. In the language of the GDA algorithm, the "ground" is the best solution value, and the water level above the ground is the threshold within which non-improving moves are allowed. The idea is to lower the ground level, and along the way, lower the water level, to allow

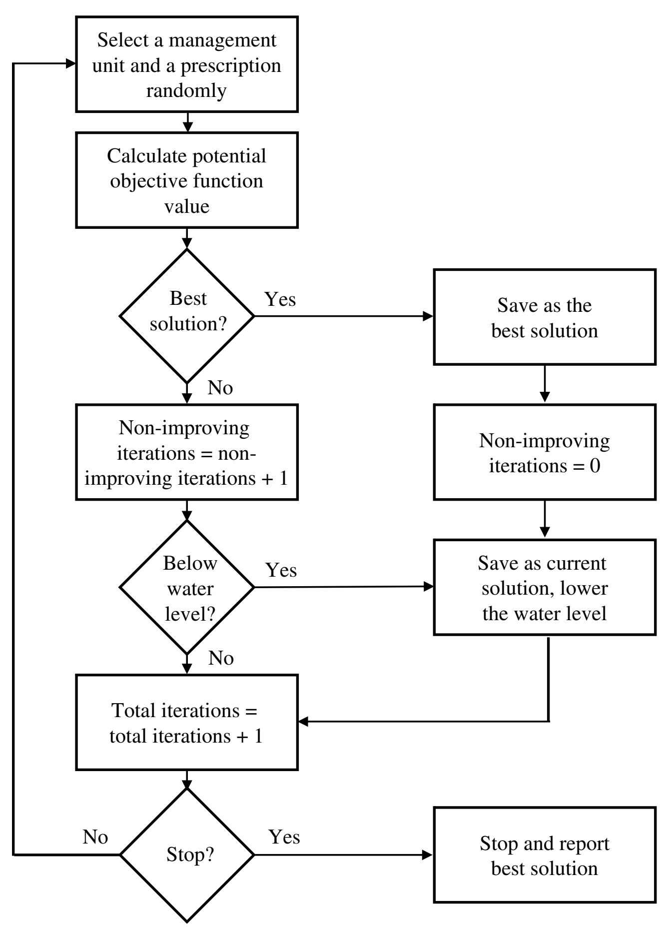

Fig. 1. Flow chart of the great deluge algorithm search process.

Table 1
Parameters used in conjunction with the great deluge algorithm

	Pattern of activities			
	Dispersed	Clumped	Random	Regular
Operational management prescriptions, low volume target				
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	5,000,000	5,000,000	5,000,000
Operational management prescriptions, high volume target				
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
Fuels reduction management prescriptions, low volume target				
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

fewer and fewer non-improving moves as the quality of the forest plan increases. Three stopping criteria were used in the modified version of GDA: total iterations, number of non-improved iterations, and the ending water level. Extensive parameterization of the GDA heuristic was required for each type of forest planning problem considered, and the parameters associated with these stopping criteria are provided in Table 1. Nine combinations of weights for each portion of the objective function were tested $(0.9, 0.8, 0.7, \ldots,$ and $0.1)$ to determine the most appropriate weights for both parts. From these trial runs, two weight values ($WH = 0.4$ and $WD = 0.6$) were chosen for further investigation. 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).

2.1.2. Clumped pattern of fuel management activities

A clumped pattern of treated areas was assumed to be one where management units are clustered on landscape. Here, we attempt to minimize the total distance between management units while also minimizing the deviation between actual harvest volume and the target harvest volume. Thus, (1) was modified by adding the two portions of the objective function as follows:

$$\text{Minimize}\quad WH\sum_{t=1}^{T}\left(\left|\left(\sum_{i\in N_t}H_{it}\right)-TV_t\right|\right)+WD\sum_{t=1}^{T}\left(\sum_{i\in N_t-1}\sum_{j\in N_t}D_{ij}\right). \tag{2}$$

Individual management unit harvests are much smaller than the target harvest levels. It may be obvious that if one management unit is harvested, $D_{ij} = 0$, however, the other half of the objective incurs such a large penalty that the solution is not optimal. More management units need to be harvested to reduce the deviation of actual scheduled harvest (H_{it}) to the target (TV_t). This, of course increases D_{ij}, but it is a balancing act – create the harvest nearest the target, yet minimize the distance from one harvest to the next. A similar interpretation of model 1 can be made. Some of the parameters related to the GDA 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 for further consideration.

2.1.3. Random pattern of fuel management activities

A random pattern of treated areas is one where management units are placed on the landscape with no regard to where other treated areas are placed. Within the GDA scheduling process, management units are randomly chosen and random prescriptions are assigned to them. Therefore, we removed the dispersion objective from (1), and solutions generated are now assumed to have random pattern across the landscape, although the pattern may be influenced by the distribution of vegetation types in the study area. The only criterion then, for evaluating the acceptability of a solution, is the deviation between actual harvest volume and the target harvest volume. Thus, the latter portion of (1), which corresponds to the dispersion of management units, is not necessary in the objective function

$$\text{Minimize}\quad \sum_{t=1}^{T}\left(\left|\left(\sum_{i\in N_t}H_{it}\right)-TV_t\right|\right). \tag{3}$$

2.1.4. Regular pattern of fuel management activities

In general, a regular pattern of treated areas would be defined as the optimum dispersed pattern. However, we imply a systematic spacing of treatments here, which would not be guaranteed by maximizing dispersion (1). Therefore, 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 the same distance to four neighboring units (northern, southern, eastern, and western). The "interval," therefore, could be defined as a desired distance between centroids of management units that produces an ideal regular pattern. The dispersed pattern we described above attempts to develop a pattern of treatments spread as far apart as possible. Ideally, the result would be a perfect grid of treatments, but not necessarily so, since the heuristic is selecting from the set of operational, irregularly shaped management units. The scheduling process associated with the regular pattern of treatments forces a perfect grid (systematic spacing) of treatments on the landscape, which is difficult given the condition of each management unit (i.e., how much harvestable timber each management unit contains). To enable one to generate such a perfect pattern, a novel approach was developed and utilized for dispersing management units. The approach is described in Kim and Bettinger (2005), yet in this preliminary work tabu search was used, since it was expected to be more computationally efficient than other heuristics. However, tabu search was not computationally efficient for these problems, although it was capable of producing high quality results. For this and other reasons mentioned earlier, GDA was selected to schedule activities for this pattern of fuels management.

In this GDA process, management units to be included in a regular pattern are chosen before prescriptions are assigned to them. This process has its drawbacks in synchronizing treatment schedules over time, and therefore we concentrate only on scheduling treatments to units in a regular pattern in the first decade of a forest plan. Scheduling a regular pattern of activities, and (a) using stands as the basic planning unit, (b) while attempting to meet timber harvest objectives, and (c) while attempting to synchronize timing of the thinnings and partial harvests available to a stand, may be one of the most complex problems we have addressed in forest planning. The main challenge here is that the management prescriptions available for each stand were not from a set that included alternatives with flexible harvest entry timing. The timing of entries into a stand was determined using a stand-level optimization program (Bettinger et al., 2005) that sought to maximize stand density targets subject to several operational constraints. As a result, locating a perfectly regular pattern of activity that (a) allowed an action to occur in a stand, and thus (b) contributed to the broader wood flow goal was extremely difficult. As a compromise, we limited our work with this pattern to the scheduling of activities during the first decade.

Since assigning a prescription to management units has no influence on the dispersion of management units, the dispersion of management units is not an essential element of the objective function. The objective function is therefore

$$\text{Minimize} \quad \left| \left(\sum_{i=1}^{N} H_{i1} \right) - TV_1 \right|. \tag{4}$$

For this process, an initial "seed" unit is chosen randomly, the grid of regular units is built, then the process described in Fig. 1 is used, except only those units included in the regular pattern are assigned management prescriptions. By using this reasoning, a solution that guarantees a nearly perfect regular pattern is obtained. This process is repeated a large number of times (100), by selecting seeds from the population at random and without replacement, thereby creating numerous regularly spaced grids of treatments for the first decade. The best set of treatments (i.e., the set that best meets the target harvest volume) is stored in memory and reported when the process has completed.

Since a limited amount of information was available to specify the most efficient spatial interval between management units for reducing wildfire hazard, several intervals were tested. From the test trials, we found that the amount of harvest volume is highly associated with the interval. A set of intervals (1.0, 1.5, 2.0, 2.5, 3.0, 3.5, 4.0, 4.5, and 5.0 km) were subsequently assessed through numerous trials of the model. When using the operational management prescriptions, 1.5 km was selected as the most appropriate interval for the high volume target, and 4.5 km for the low volume target. When using the fuels reduction management prescriptions, 3 km was selected as the most appropriate interval for the low volume target. This produces a tighter arrangement of treatments in a regular pattern (as compared to using the operational prescriptions with the same volume target), because less timber volume is harvested in each treatment unit when using the fuels reduction management prescriptions.

One of the main differences between this work and that of Bettinger et al. (2007) is that sum of squared deviations was used in the latter to develop the highest, and most even timber harvest in each time period. The Bettinger et al. (2007) model include only the one objective, and it sought to maximize the potential harvest opportunities. A squared deviation is frequently used in forest planning literature to facilitate a better "even" harvest when then upper harvest level is unknown. In the current work, the harvest targets were well below the maximum potential harvest opportunities, therefore we simply sought to determine the absolute difference between the actual scheduled volume and the target. In addition, since we used a bicriteria model for two of the spatial patterns, a similar structure was used in modeling the other two spatial patterns.

2.2. Point pattern analysis: nearest neighbor distance

The nearest neighbor distance analysis, which is one of a set of point pattern analysis techniques (Boots and Getis, 1988; Cressie, 1993) was used to assess whether the scheduled patterns actually could be validated on the landscape. Here, the observed mean nearest neighbor distance from scheduled management activities was compared to a statistic which describes the expected mean nearest neighbor distance for a random pattern

$$d_{\text{exp}} = 0.5\sqrt{\frac{LSA}{N}}, \tag{5}$$

where d_{exp} = expected mean nearest neighbor distance for a completely random pattern, LSA = area of the landscape, N = total number of management units scheduled for treatment.

The hypothesis is that a pattern would be random if the observed mean nearest neighbor distance was not significantly different from the expected mean for a random pattern. If the observed mean was significantly less than the expected mean, the pattern would be considered clumped; 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

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

where $\hat{d}_{obs}$ = observed mean distance of neighboring treated units, $\text{var}(\hat{d})$ = variance, or $\left(0.0683\left(\frac{LSA}{N^2}\right)\right)$.

2.3. Study site description

The study site is the Grand Ronde River Basin (approximately 178,000 hectares) in northeastern Oregon (USA) (Fig. 2). Most of the area is managed by the US Forest Service (Wallowa-Whitman National Forest), however some private land exists in the center of the basin. Geographic information system databases representing the management units of the study area were acquired from the Interior Northwest Landscape Analysis System project (LaGrande Forestry and Range Sciences Lab, 2000). When scheduling activities across the landscape, centroids of management units (polygons) were used as a proxy for their locations. In addition, scheduling of fuel management activities required attribute data that describes the specific vegetation structure of each management unit (tree lists). Data regarding stand structure and available harvest volume for each management unit are essential in scheduling forest management activities, and were also acquired from the Interior Northwest Landscape Analysis System project. Changes in stand condition and harvest volume from several management activities were simulated over 10-year periods (100 years) using a stand-level optimization model (Bettinger et al., 2005).

Two sets of management prescriptions were tested in this research. The first approach was to use operational management activities, and the second approach was to use management prescriptions designed specifically for fuel reduction purposes. The operational management prescriptions were developed with the goal of maintaining stand density levels within a target range (35–55% Stand Density Index), which is now preferred on government land in the study region over the design of prescriptions that maximize net present value. A stand-level optimization process for

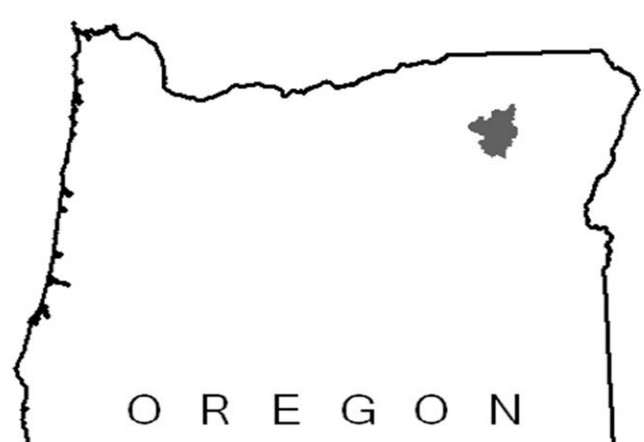

Fig. 2. Study site area, Upper Grande Ronde River Basin, Oregon (USA).

Table 2
Operational stand-level management prescriptions for the study area

Management prescription	Residual basal area (m^2/ha)	Minimum volume (m^3/ha)	Harvestable range	
			Upper diameter (cm)	Lower diameter (cm)
1	18.4	0	0.0	17.8
2	13.8	0	53.3	17.8
3	18.4	21	0.0	17.8
4	18.4	42	0.0	17.8
5	18.4	63	0.0	17.8
6	13.8	21	53.3	17.8
7	13.8	42	53.3	17.8
8	13.8	63	53.3	17.8
9	16.1	63	76.2	12.7

developing efficient management regimes that uses dynamic programming and a region-limited search strategy was previously described in the literature (Bettinger et al., 2005). The stand-level process develops management regimes by penalizing deviations from a preferred range of stand density. Operational considerations, such as minimum harvest levels and harvestable diameter ranges, are also important, and a range of these were considered as constraints in this modeling process, based on discussions with managers in the region (Table 2). Subsequently, 10 prescriptions (including a no treatment prescription) were utilized in the first approach.

Two management prescriptions for fuel reduction purposes were designed, with the goal of maintaining a desired stand density target by thinning small-diameter trees. The harvestable diameter limit ranges were (1) 2.5–17.8 cm, and (2) 2.5–25.4 cm. These two management prescriptions included a residual basal area constraint of 18.4 $m^2\,ha^{-1}$ and the need to maintain stand density within a specific range (35–55%). Since these are designed to reduce certain types and sizes of fuels, no minimum volume constraint was employed. Two additional management prescriptions of 'thinning followed by prescribed fire' were produced by modify-

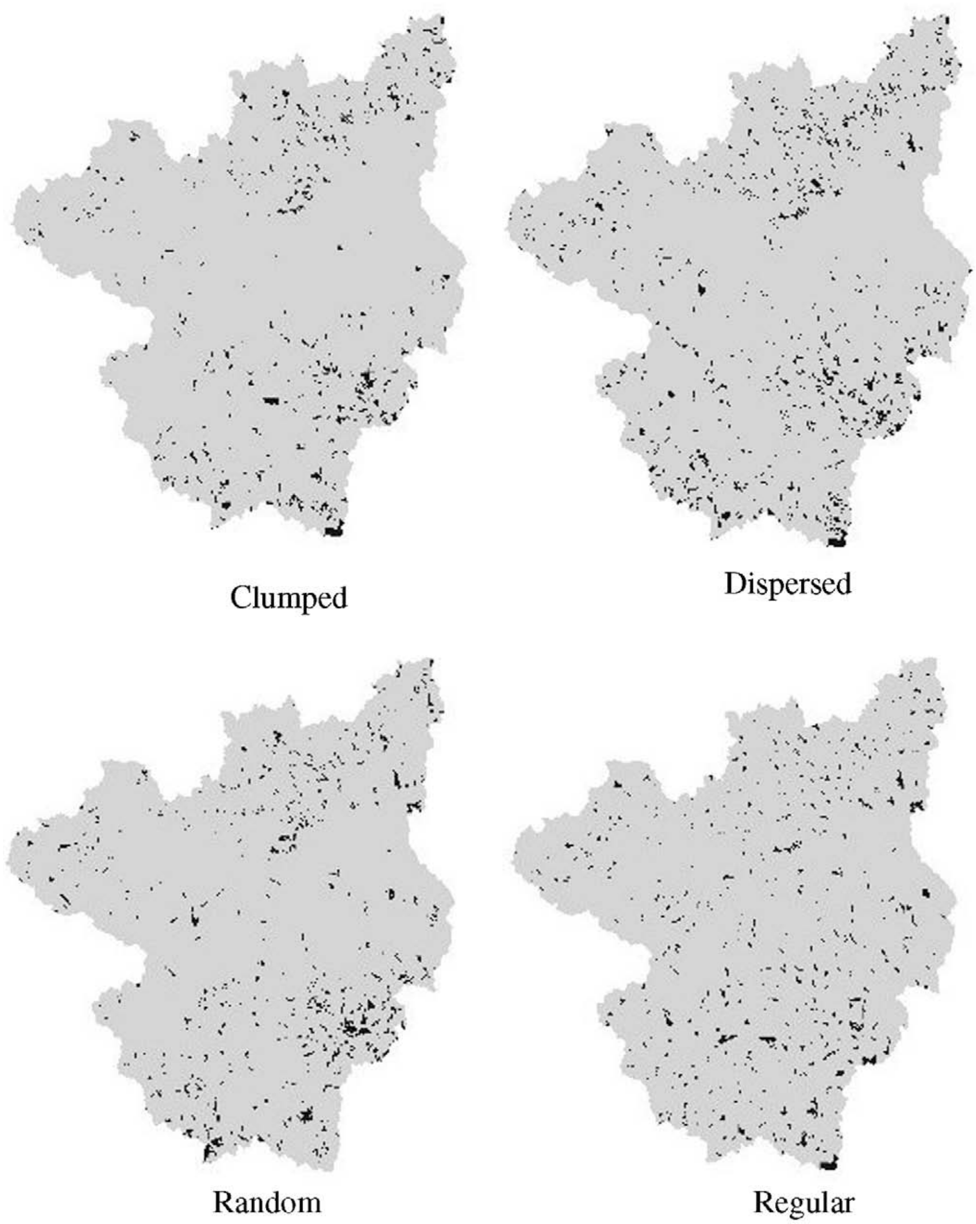

Fig. 3. Pattern of treated management units in the first decade, using the high volume target and the operational management prescriptions.

ing the 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 m in height were assumed killed (van Wagtendonk, 1996; Stephens, 1998). Using these assumptions, all trees less than 2 m in height were removed from the associated tree lists in the period of treatment. Subsequently, five prescriptions (including a no treatment prescription) were utilized in the second approach. These prescriptions were also developed using the stand-level optimization process found in Bettinger et al. (2005).

2.4. Wildfire simulations

To quantify changes in simulated wildfire behavior resulting from spatial patterns of management activities, a fire growth simulation model, FARSITE (Finney, 1998) was used. FARSITE requires spatial information regarding topography and fuels, as well as weather parameters (in this case, those that describe a severe weather condition for fire). Weather parameter inputs to FARSITE were constant. The only variable data were the representations of the fuels across the landscape as a result of scheduling management activities in patterns. Our modeling system integrated the scheduling process (GDA) with FARSITE; we obtained the FARSITE code from the developers to facilitate the integration. Landscape representations of forest fuels were automatically generated based on each forest plan developed with the GDA heuristic. Within our integrated modeling system, the transfer of data to FARSITE was therefore seamless. FARSITE generates outputs describing simulated wildfires and their behavior, including fireline intensity, rate of spread, and flame length. In our analysis, flame lengths and fireline intensity were primarily used to compare the treatment effects. To assess the effects of spatial patterns of management activities, 15 wildfires with different ignition points were simulated with the assumption that they all occur in the first decade.

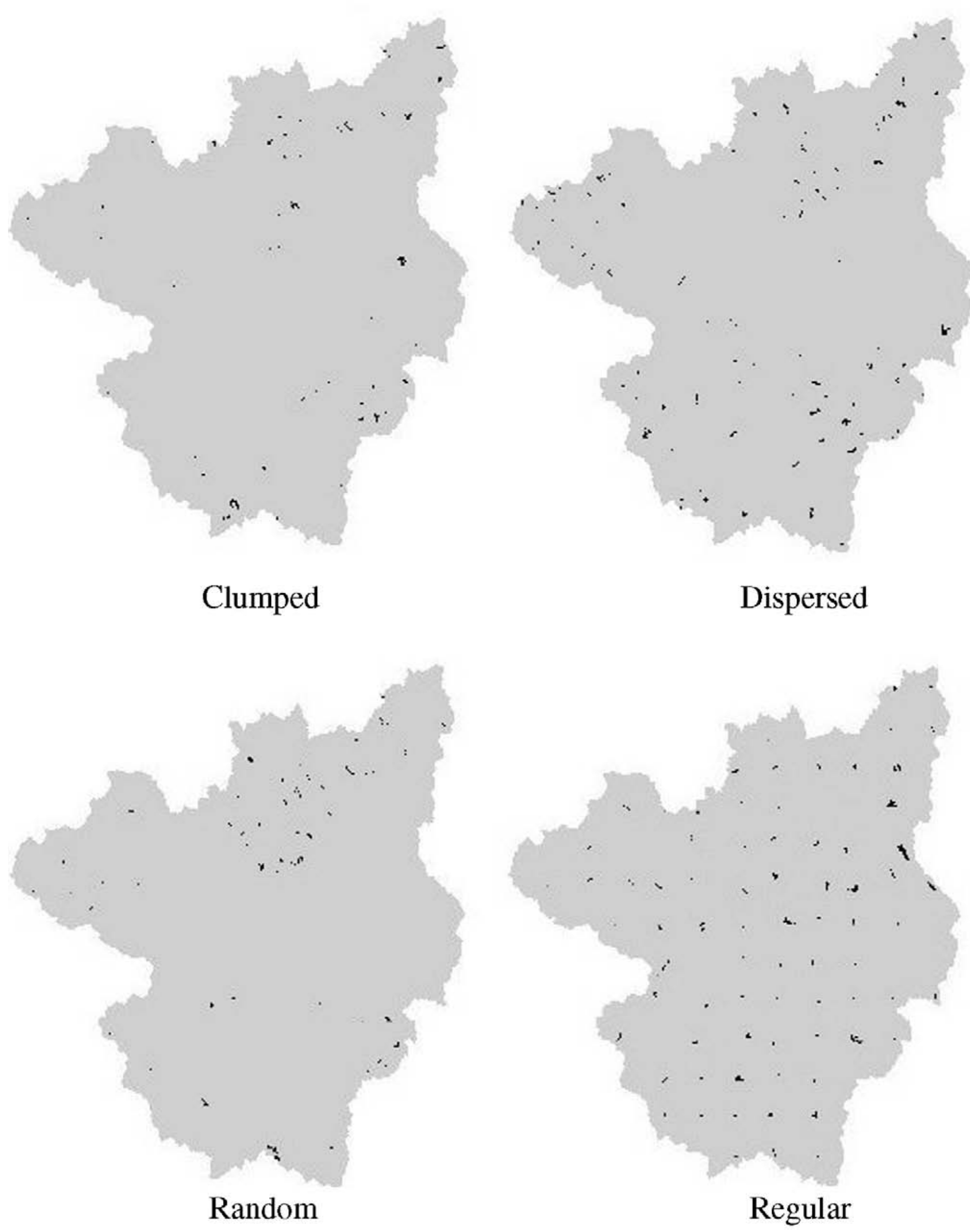

Fig. 4. Pattern of treated management units in the first decade, using the low volume target and the operational management prescriptions.

The 15 ignition points were selected randomly and applied to every forest plan developed using the four patterns of treatment activities when operational management prescriptions were used. When fuel reduction management prescriptions were used, 15 different ignition points were randomly selected and applied.

Each of the scheduling and subsequent wildfire simulations were completed using a personal computer with a 2.4 GHz processor and 1.5 Gb of RAM. To perform a single 100-year simulation and to model 15 wildfires in the first decade, 286 min were required, on average, for the dispersed pattern, 88 min for the clumped pattern, 138 min for the random pattern, and 6 min for the regular pattern. The bulk of the processing seemed to be in locating the best spatial pattern of management prescriptions and that produced the most desirable harvest level.

3. Results

The results of spatially optimizing the placement of fuel management activities, and their subsequent effects on simulated wildfires, are divided into those simulations that utilized the operational management prescriptions and those that utilized the fuels reduction management prescriptions. In each case a target timber volume was desired in each time period, thus while the fuels reduction management prescriptions targeted smaller diameter trees, commodity production was incorporated into the objective of each resulting forest plan.

3.1. Operational management prescriptions

The pattern of management units that were scheduled for treatment in the first time period (decade) using the high volume target are shown in Fig. 3, while those using the low volume target are shown in Fig. 4. The distinction between the spatial patterns can be visually verified when the low target volume (5% of maximum) is applied, however the distinction between patterns is more vague when using the high target volume (50% of maximum). The solutions generated for the high volume target included a higher number of treated management units (Table 3) and almost five times the treated area, as compared to those generated for the low volume target. Since the high volume target was five times the low volume target, this was expected. The treatments, in the case of high volume target, occupied a small portion (3.1–6.5%) of the entire study region in each decade. In the case of the low harvest volume target, the treated area ranged from 0.5% to 1.0% per decade.

Point pattern analysis revealed some limitations of this modeling approach (Table 3). While the regular pattern was validated for both the low and high target volume, most other patterns were not, except the random pattern using the low volume target and the clumped pattern using the high volume target. For the clumped pattern, we expected to see (and found) a lower observed distance between management units than the expected distance of the random distribution, however the difference between the observed and expected was not significantly different in the case of the low volume target. The dispersed pattern was not confirmed, nor validated using the point pattern analysis. To provide the suggested harvest volume over time while forcing units apart (dispersed) required more management units to be scheduled. To provide the suggested harvest volume over time while forcing units to be close to one another (clumped) required fewer management units to be scheduled. As a result, the observed and expected distances are not comparable between the spatial patterns.

The best solutions from the four spatial patterns simulated an acceptable even-flow harvest level (Table 4), however the best solution using the dispersed pattern had much more variable harvest volumes, due to the management prescriptions available, the initial forest structure, and the desire to spread the treatments as far apart as possible. As a result, 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 were available in subsequent time periods. This compounded the ability to actually produce a dispersed pattern of management activities.

Most of spatial patterns reduced wildfire sizes when FARSITE was used to model 15 wildfires in the first decade (Table 5). However, there was little other evidence of treatment effect on wildfire behavior, as indicated by the severity of wildfires (i.e., flame length

Table 3
Results of the point pattern analysis for scheduled patterns of activities in the first decade of the planning horizon when using the operational management prescriptions

	Pattern of activities			
	Dispersed	Clumped	Random	Regular
Low volume target				
Number of units treated	218	56	81	88
Observed distance (m)[a]	1,418	2,642	2,553	3,804
Expected distance (m)[b]	1,430	2,822	2,346	2,251
z-Statistic	−0.2	−0.9	1.5	12.4
Conclusion	Pattern Invalid (random)	Pattern Invalid (random)	Pattern Valid	Pattern Valid
High volume target				
Number of units treated	967	456	614	476
Observed distance (m)[a]	603	871	753	1,150
Expected distance (m)[b]	679	989	852	968
z-Statistic	−6.7	−4.9	−5.5	7.9
Conclusion	Pattern Invalid (clumped)	Pattern Valid	Pattern Invalid (clumped)	Pattern Valid

[a] Nearest neighbor average distance between the centroids of treated management units.
[b] Expected average nearest neighbor distance for complete randomness.

Table 4
Harvest volume (m^3) per decade of the best solution generated for each spatial pattern of activity when using the operational management prescriptions

	Pattern of activities			
	Dispersed	Clumped	Random	Regular
Low volume target				
Decade 1	57,848	56,631	56,625	56,625
Decade 2	57,016	56,625	56,625	–
Decade 3	56,563	56,619	56,625	–
Decade 4	58,080	56,625	56,625	–
Decade 5	57,514	56,625	56,625	–
Decade 6	57,395	56,625	56,625	–
Decade 7	58,171	56,625	56,625	–
Decade 8	56,178	56,636	56,631	–
Decade 9	57,650	56,625	56,625	–
Decade 10	57,078	56,631	56,625	–
High volume target				
Decade 1	584,915	566,257	566,251	566,251
Decade 2	489,717	566,251	566,251	–
Decade 3	542,571	566,251	566,251	–
Decade 4	574,592	566,251	566,251	–
Decade 5	596,359	566,251	566,251	–
Decade 6	595,623	566,251	566,251	–
Decade 7	643,160	566,251	566,251	–
Decade 8	583,460	566,257	566,251	–
Decade 9	608,732	566,251	566,251	–
Decade 10	543,335	566,240	566,251	–

Table 5
Wildfire simulation results using the operational management prescriptions

	Pattern of activities			
	Dispersed	Clumped	Random	Regular
Low volume target				
Flame length (m)	1.02	1.02	1.02	1.01
Change from control (m)	0	0	0	−0.01
Fireline intensity (BTU/ft/s)	429.5	427.9	428.5	419.7
Change from control (BTU/ft/s)	+1.7	+0.1	+0.7	−8.1
Average fire size (ha)	1287	1289	1287	1395
Change from control (ha)	−2	0	−2	+106
High volume target				
Flame length (m)	1.03	1.02	1.02	1.03
Change from control (m)	+0.01	0	0	+0.01
Fireline intensity (BTU/ft/s)	435.8	430.0	434.1	434.8
Change from control (BTU/ft/s)	+8.0	+2.2	+6.3	+7.0
Average fire size (ha)	1258	1276	1275	1253
Change from control (ha)	−31	−13	−14	−36

and fireline intensity). With the exception of the regular pattern applied with the low target volume, none of the spatial patterns were able to reduce flame length or fireline intensity. Of course, severity of wildfire behavior was reduced within management units of treatments, but the overall severity of wildfires burning across a larger landscape was not much affected by the spatial pattern of treatments.

Two conclusions were drawn from this work: (1) the operational management prescriptions, with stand density goals and other commodity production emphases, may not be appropriate for reducing forest fuels levels and subsequently mitigating wildfire behavior during severe wildfire seasons, and (2) the high target volume obscures the spatial pattern of treatments. Given these results, no further analysis of the wildfire simulations (when using the operational management prescriptions) was pursued. However, we developed the fuels reduction management prescriptions for each management unit to determine whether landscape-level

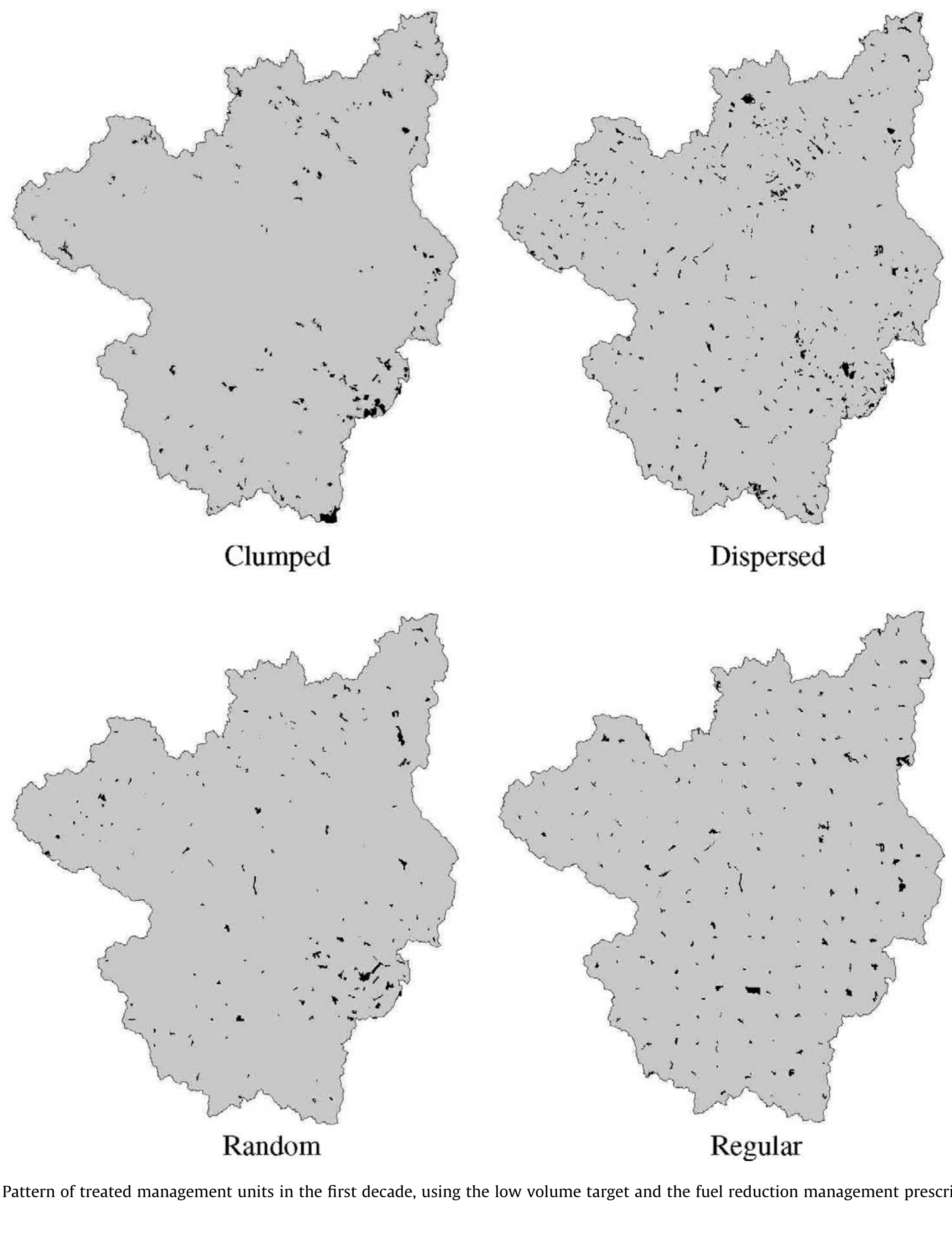

Fig. 5. Pattern of treated management units in the first decade, using the low volume target and the fuel reduction management prescriptions.

effects of patterns of activities on simulated wildfires can be observed. Since the time required to generate 30 simulations of each pattern was extensive, we also concentrated the subsequent analyses on the low harvest volume target. The lower harvest volume objective is also more realistic in today's planning environment.

3.2. Management prescriptions designed specifically for fuel reduction purposes

The best solutions generated by the scheduling model could generate each spatial pattern of fuel management activities fairly well (Fig. 5). The point pattern analysis (Table 6) provided a statistical verification of most of the patterns (clumped, random, and regular patterns). The dispersed pattern required a larger number of management units to reach the harvest goal, and the pattern therefore became less distinct, and more like the random pattern. The best solutions of the four spatial patterns produced an almost exact even-flow harvest level for the low target volume, thus the scheduling model handled even-flow and spatial pattern objectives appropriately. Using the operational management prescriptions, the scheduling model had a tendency to increase the number of treatment units when optimizing the dispersed pattern, and the same tendency was found here. The number of treatment units scheduled for the dispersed pattern was almost double compared to other patterns (Table 6). Therefore, this might be an issue if other economic or environmental concerns arise in scheduling fuel management treatments.

According to the wildfire simulation results (Table 7), wildfire behavior was altered in most cases by treatment activities scheduled in spatial patterns. The treatment activities were most effective in reducing overall fire sizes when they were spatially arranged in the dispersed or the clumped pattern. Most spatial patterns marginally reduced the flame length and fireline intensity, which indicated the severity of wildfires. The simulation results showed that the regular pattern was most effective in reducing fireline intensity.

These results indicate marginal changes in wildfire behavior, and may be simply due to chance. While the wildfires all use the same ignition points, the location of treated units varies, thus an opportunistic placement of an activity near an ignition point may have affected wildfire behavior results. Therefore, we investigated the wildfire simulations further. Rothermel and Rinehart (1983) introduced an interpretation of wildfire behavior, in which flame length and fireline intensity were classified into four severity classes (Table 8). Among the four classes, classes 3 and 4 were considered severe, and a wildfire in these classes is assumed not to be controllable. We expected to find that the fuel reduction management prescriptions would reduce the areas classified as being severe. However, compared to the control solution, the activities scheduled in the four spatial patterns all were marginally effective in reducing the severe wildfire characteristics (Table 9). The burned areas from the wildfire simulations were then classified into those that were inside fuels management treatment units, and those that were adjacent to the treatment units (grid cells sharing an edge). According to these results (Table 10), simulated wildfires contacted treatments most often when treatments were scheduled using a dispersed pattern. Here, 2.22% of the wildfires

Table 6
Results of the point pattern analysis for scheduled patterns of activities in the first decade of the planning horizon when using the fuels reduction management prescriptions

	Pattern of activities			
	Dispersed	Clumped	Random	Regular
Low volume target				
Number of units treated	591	264	346	191
Observed distance (m)[a]	878	360	1073	1748
Expected distance (m)[b]	868	1299	1135	1527
z-statistic	0.5	−22.5	−1.9	3.8
Conclusion	Pattern Invalid	Pattern Valid	Pattern Valid	Pattern Valid

[a] Nearest neighbor average distance between the centroids of treated management units.
[b] Expected average nearest neighbor distance for complete randomness.

Table 7
Wildfire simulation results using the fuels reduction management prescriptions[a]

	Pattern of activities			
	Dispersed	Clumped	Random	Regular
Low volume target				
Flame length (m)	1.09	1.09	1.09	1.09
Change from control (m)	0	0	0	0
Fireline intensity (BTU/ft/s)	177.3	177.4	177.5	176.7
Change from control (BTU/ft/s)	−0.7	−0.6	−0.5	−1.3
Average fire size (ha)	2116	2114	2127	2123
Change from control (ha)	−10	−12	+1	−3

[a] These 15 simulated wildfires had different ignition points than the ones simulated using the operational management prescriptions.

Table 8
An interpretation of fire behavior[a]

Fire severity class	Flame length (m)	Fireline intensity (BTU/ft/s)	Interpretation
1	<1.2	<100	Fires can generally be suppressed by persons using hand tools at the head or flanks of fires
2	1.2–2.4	100–500	Fires are too intense for direct suppression at their head by persons using hand tools Equipment or vehicles would be required for suppression
3	2.4–3.4	500–1000	Fires may start torching out, crowning, or spotting. Suppression at the head of the fire would probably be ineffective
4	>3.4	>1000	Crowning and spotting occur. Suppression efforts at the head of the fire are ineffective

[a] From Rothermel and Rinehart (1983).

Table 9
Wildfire simulation results for the average fire, by fire severity class

	Pattern of activities				
	Control	Dispersed	Clumped	Random	Regular
Flame length					
Severity class 1 (ha)	1521	1513	1514	1521	1521
Severity class 2 (ha)	383	383	380	385	382
Severity class 3 (ha)	131	130	130	130	130
Severity class 4 (ha)	91	90	90	91	90
Fireline intensity					
Severity class 1 (ha)	1464	1460	1458	1466	1466
Severity class 2 (ha)	433	430	429	434	431
Severity class 3 (ha)	131	130	130	130	129
Severity class 4 (ha)	98	96	97	97	97

Fuel reduction management prescriptions, low volume target.

Table 10
Wildfire area within and around treated management units (fuel reduction management prescriptions, low volume target)

	Pattern of activities			
	Dispersed	Clumped	Random	Regular
(A) Area in treated units (ha)	24	11	9	17
(B) Area adjacent to treated units (ha)	23	9	8	13
(C) Area outside, and not adjacent to treated units (ha)	2069	2094	2110	2094
(D) Burn ratio[a]	2.22	0.95	0.78	1.39
(E) Number of treated units	591	264	346	191
(E) Treatment effectiveness ratio[b]	0.08	0.08	0.05	0.16

[a] ((A + B)/(A + B + C)) * 100.
[b] ((A + B)/E).

contacted, or were adjacent to, treated areas. Of course, one should keep in mind that the dispersed pattern required many more treatment units than the other patterns required to obtain the targeted harvest volume. Therefore, the most efficient interaction of treated units and burned areas seems to be with the regular spatial pattern, given the number of treated units and the amount of burned areas within, or adjacent to those units.

4. Discussion

The integrated modeling effort developed in this research represents a unique contribution of spatial modeling to the field of forest planning. The solutions generated by the scheduling model provided a spatially optimized allocation of treatment activities across a large landscape, and an evenly distributed harvest volume throughout the multi-decade time horizon, but also facilitated subsequent wildfire simulations. Some of the patterns of treatments allocated across the landscape were not only verified in a visual assessment, and also found statistically valid. However, the subsequent analyses of effects on wildfire behavior were not as significant as we had hoped. We had hoped that management prescriptions arranged in spatial patterns might be effective in mitigating simulated landscape-scale wildfire behavior, yet found that operational management prescriptions were ineffective and fuels management prescriptions were marginally effective. We had also hoped to find that the effects of management activities on simulated landscape-scale wildfire behavior would be different among the spatial patterns considered, yet found that there were only minor differences in the dispersed, clumped, and regular patterns. Each of these patterns was, however, more effective than the random pattern of management activities, which could be interpreted as the current management practice.

Some of the patterns of fuels management activities were not statistically significantly different from other patterns we generated. The nearest neighbor analysis we used to determine patterns examines the distances between a point (here, the centroid of a forest stand) and the closest point(s) to it, and then compares these values to expected values from a random sample of points. The method is a common method for measuring the distance to nearest neighbors and inferring pattern. Since forest stands are the basic planning unit, and since the distance from one treated stand to the next treated stand should be assessed to determine whether they are dispersed or clustered, this test seemed like the logical choice. From a visual perspective, the patterns we anticipated seemed to have been created. However, from an analytical perspective, we could not confirm that the patterns were statistically significant. Other statistical measures may have been employed, such as the K-function (which focuses on the variance of distances), Knox statistic (to determine significant clustering), or other refined methods that examine the difference between observed and expected distributions, spatial autocorrelation, or spatial association. However, we limited our validation work to the nearest neighbor analysis and subsequent validation. As a consequence, our failure to detect formation of landscape patterns at high levels of scheduled activities may be related to our choice of statistical method.

The main reason that might have caused the lack of a significant treatment effect of the spatial arrangement of operational management prescriptions on wildfire behavior was that they were not designed to do so. The operational prescriptions were designed to control stand densities through thinning, using several operational considerations. No consideration was given to specifically managing ladder, crown, or surface fuels. These prescriptions, which consisted of periodic thinnings of various portions of the diameter distribution of each stand, might have contributed to a reduction in ladder or crown fuels, but likely increased surface fuel loads. Therefore, additional management prescriptions, in which surface and ladder fuels were specifically managed, were developed and tested. Those who pursue additional simulations of this type should keep in mind that the spatial pattern of activity will become lost with an increased number of management activities scheduled across the landscape.

According to wildfire simulation results using the fuels reduction management prescriptions, the cumulative effects of the fuel management prescriptions marginally altered wildfire size and severity across the landscape. These management prescriptions were intended to remove the smaller diameter trees from each stand, with the goal of reducing the ladder fuels. Subsequent prescribed fires reduced both the surface fuel loads and the smaller diameter trees that were not removed through harvesting. We hypothesized that by modeling these prescriptions across the landscape, albeit in a spatial pattern, some aspects of simulated wildfires would be altered. Unfortunately, at the target harvest level we modeled, we have to reject the notion that when limited fuels management treatments are implemented broadly across the landscape, wildfire behavior can be modified.

Our conclusions do not suggest that a more intense implementation of fuels management treatments across a landscape will be ineffective. They simply suggest that if budgets for these types of programs are limited, and if managers decide to spread these treatments across the landscape with the hope of mitigating wildfire behavior, any one spatial pattern may be as effective as the others for reducing the impact of wildfires during a severe fire season. While the regular pattern may provide the most efficient treatment option, in terms of treatment unit interaction with wildfire, one is left to wonder whether the attention to the spatial pattern is worth the level of planning that must go into the program. As we noted earlier, scheduling a perfectly regular pattern of activities, using stands as the basic planning unit, and attempting to meet timber harvest objectives with a limited set of available management prescriptions, is a very complex problem. Maintaining the perfect pattern over time is an issue that would need to be addressed every 10–20 years, which is consistent with the timing of typical US National Forest Plan revisions. Further research is necessary to determine how these effects may unfold during non-severe wildfire seasons.

While we recognize that modeling a wood flow objective may not be the optimal course of action for US National Forests, strategic plans for US National Forest plans generally fail to identify the relationship between goals, goods and services, and direction, and further fail to provide operational guidance to project-level management efforts, all of which may be needed as inputs to tactical management plans (Rauscher et al., 2000). One of our assumptions was that while applying fuels reduction broadly treatments across the landscape may be the best course of action when it comes to reducing the threat of fire, in times of limited budgets managers may need to assess other options. Therefore we illustrated here how a spatial arrangement of treatments can be applied under a limited set of treatment intensities, as represented by wood flow targets.

Our approach for developing fuels management plans was one that relied on a single type of heuristic method for scheduling activities. An exploration of alternative solution approaches might enhance this work, since one can hypothesize that a different method may be necessary for scheduling different patterns activities across the landscape. For example, the great deluge algorithm might be more effective in scheduling dispersed treatments, while a genetic algorithm may be more effective in scheduling clumped treatments. We openly acknowledge this limitation and the underlying uncertainty it may cause, however since our objective was to illustrate how forest fuel management activities can be scheduled across the landscape, we leave this area of exploration for others to pursue.

5. Conclusions

The contribution of this work to the body of operational research sciences lies in the integration of spatial patterns of scheduled activities into a planning framework, and the coordination of fire simulations with forest harvest scheduling techniques. Thus far, no other research has attempted to perform these analyses at the landscape-scale. The modeling process developed in this research provides approaches in which management activities, both operational and those designed specifically for fuel reduction purposes, were scheduled in spatial patterns across a large landscape. The solutions optimized through the scheduling process present a range of patterns of treatments across the landscape while also providing an evenly distributed harvest volume through time. The scheduling model produced some meaningful results and provided an application of spatial modeling concepts to fuel management activities. Unfortunately, we found through statistical analysis that some of the desired patterns of activity are not valid due to the nature of the problem (multi-objective with volume goals). However, visual examinations suggest that the patterns are being represented fairly well, even though they are not statistically significant.

The typical operational prescriptions used in this research were aimed at controlling the stand density by utilizing periodic thinnings. These were developed in conjunction with a larger landscape planning project and contained operational constraints typical for the region. According to the wildfire simulation results, significant differences in wildfire behavior will rarely be achieved when using these prescriptions, since 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 wildfire behavior. Therefore, if reducing fire hazard were an important management goal, it would seem important to adopt additional management prescriptions that have the intent of controlling the critical fuels. These management prescriptions, scheduled in a pattern across the landscape, provide marginal reductions in wildfire behavior. However, it is not clear how much treatment is needed to significantly disrupt the progress of wildfire. In further studies, more attention to these remaining issues should be paid.

Given time constraints, we were unable to perform a large range of simulations beyond the 360 or so that were developed for this analysis. As a result, a trade-off analysis between treatment intensity (as reflected by the harvest target) and fire intensity (as reflected by flame length, fireline intensity, or fire size) was limited. The only broad-based impacts we observed between the low volume target and the high volume target were slight increases in fireline intensity and slight reductions in average fire size when using the high volume target. A more extensive analysis of the operational and fuels reduction treatments applied to varying volume targets may allow one to determine the appropriate volume target level that represents the most efficient use of resources in controlling fire behavior. We acknowledge that there may be other computational methods, such as metaheuristic optimization methods that work with populations of solutions, that may lead to more time-efficient work in this area.

At this point, without further analysis of other patterns or levels of desired harvest volumes, we can conclude that our two hypotheses are rejected. We had hoped that management activities that are scaled and arranged in spatial patterns might be effective in mitigating landscape-scale wildfire behavior. However, operational management prescriptions were ineffective, and fuels management prescriptions were marginally effective. We had also hoped to find that the effects of management activities on landscape-scale wildfire behavior would be different among the spatial patterns considered. However, we found that there were only minor differences in the dispersed, clumped, and regular patterns, yet each of these was more effective at mitigating some of the characteristics of wildfires during severe wildfire seasons than the random pattern of management activities.

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