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Restoration of fire in managed forests: a model to prioritize landscapes and analyze tradeoffs

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Abstract. Ongoing forest restoration on public lands in the western US is a concerted effort to counter the growing incidence of uncharacteristic wildfire in fire-adapted ecosystems. Restoration projects cover 725,000 ha annually, and include thinning and underburning to remove ladder and surface fuel, and seeding of fire-adapted native grasses and shrubs. The backlog of areas in need of restoration combined with limited budgets requires that projects are implemented according to a prioritization system. The current system uses a stand-scale metric that measures ecological departure from pre-settlement conditions. Although conceptually appealing, the approach does not consider important spatial factors that influence both the efficiency and feasibility of managing future fire in the post-treatment landscape. To address this gap, we developed a spatial model that can be used to explore different landscape treatment configurations and identify optimal project parameters that maximize restoration goals. We tested the model on a 245,000 ha forest and analyzed tradeoffs among treatment strategies as defined by fire behavior thresholds, total area treated, and the proportion of the project area treated. We assumed the primary goal as the protection and conservation of old growth ponderosa pine trees from potential wildfire loss. The model located optimal project areas for restoration and identified treatment areas within them, although the location was dependent on assumptions about acceptable fire intensity within restored landscapes, and the total treated area per project. When a high percentage of stands was treated (e.g., >80%), the resulting project area was relatively small, leaving the surrounding landscape at risk for fire. Conversely, treating only a few stands with extreme fire behavior (<20%) created larger projects, but substantial old growth forests remained susceptible to wildfire mortality within the project area. Intermediate treatment densities (35%) were optimal in terms of the overall reduction in the potential wildfire mortality of old growth. The current work expands the application in spatial optimization to the problem of dry forest restoration, and demonstrates a decision support protocol to prioritize landscapes and specific areas to treat within them. The concepts and model can be applied to similar problems in spatial ecology.

Key words: dry forests; forest management; forest restoration; fuel treatment; spatial optimization; wildfire hazard; wildfire risk.

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Introduction

Ecological restoration is widely regarded as essential for biodiversity conservation, particularly in human-dominated ecosystems (Jordan et al. 1988, Young 2000, Carroll et al. 2004). Decision support tools are an important component of restoration programs and are typically leveraged to facilitate the planning and prioritization of restoration investments (Noss et al.

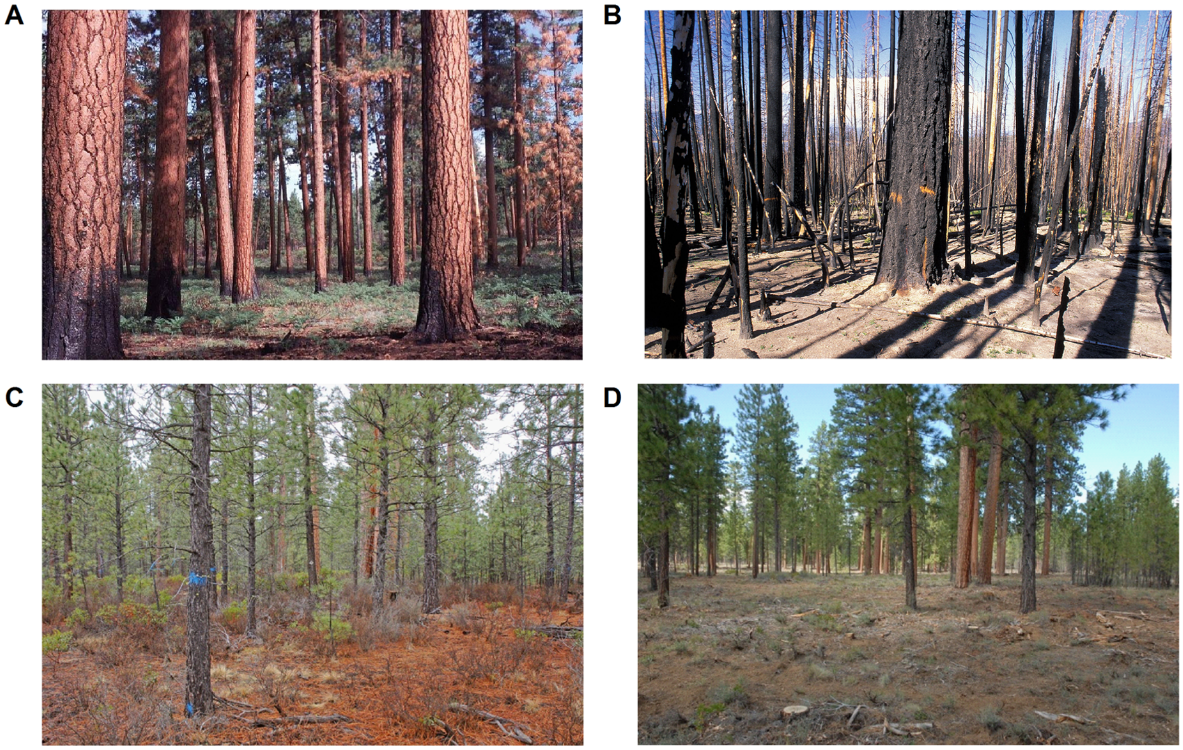


Fig. 1. Restoration and fuel treatments on the Deschutes National Forest. Stand (A) has received periodic (10–15 year) underburns to reduce tree density and ladder fuels, and represents ideal stand structure for dry forest conditions on the Forest. Stand (B) has not experienced fire or treatments in recorded history, and prior to burning in the 2004 Davis wildfire contained a substantial amount of conifer understory and shrubs resulting in crown fire and 100% tree mortality. Stands in (C) and (D) are before and after treatment in the Cosmos restoration project near the study area, showing the effects of thinning to reduce conifer and shrub density and associated ladder fuels.

2009). Depending on the goal, restoration can require substantial investments, and decision support tools and associated frameworks help ensure that the process is efficient and that restoration goals are met (Wilson et al. 2011). A large number of decision support frameworks have been discussed in the literature (Moilanen et al. 2009), many of which contain spatial and temporal dimensions to integrate landscape-scale ecological properties required to meet restoration goals.

One of the most extensive terrestrial restoration efforts concerns fire-frequent conifer forests in the western US (USDA-USDI 2001, Allen et al. 2002, Noss et al. 2006*a*, Noss et al. 2006*b*). These forests have been impacted by logging practices, grazing, and fire supression, and an estimated 25 million ha have altered fire regimes that leave them vulnerable to high severity wildfire. The majority of the 725,000 ha treated annually are fire-adapted dry conifer forests (e.g., *Pinus ponderosa*, *Pinus jeffreyi*, *Pinus lambertiana*, *Pseudotsuga menziesii* var. *glauca*, *Larix occidentalis*) that provide a multitude of ecological and ecosystem services including key wildlife habitat (Lehmkuhl et al. 2007), carbon sequestration (Hurteau et al. 2011), drinking water, and recreational values. Restoration goals include reintroducing low severity surface fire to maintain fire resilient forests and associated ecological values. Restoration activities (e.g., thinning, mastication, and prescribed fire) aim to reduce potential wildfire severity in fire excluded stands to achieve these goals (Fig. 1). The large scope of the problem combined with limited resources to accomplish restoration goals led to the development of a prioritization system for federal lands where stands that depart from the historic range of variability (HRV), as measured by a condition class score, are targeted for treatment (Rollins and Frame 2006). The prioritization system does not explicitly consider the spatial arrangement of treatments and potential contribution of treatments to the long-term goal of creating landscapes where fire can be efficiently managed without loss of important ecological values. Moreover, departure from HRV can result from many factors other than increased fuels and fire hazard (Keane et al. 2007), and therefore can potentially be misleading as a prioritization metric. While a number of studies have examined the use of spatial optimization to locate and prioritize fuel management activities (Loehle 1999, Finney 2007, Lehmkuhl et al. 2007, Parisien et al. 2007, Konoshima et al. 2008, Wei et al. 2008, Kim et al. 2009), these models address the problem of locating treatments to optimally disrupt fire spread, rather than creating fire adapted landscapes to restore fire as an ecological process.

In this paper, we present a decision support model to prioritize project areas for dry forest restoration. The model seeks to locate project areas to most efficiently reduce potential wildfire loss of fire resilient old growth ponderosa pine while creating contiguous areas within which prescribed and managed fire can be effectively used to maintain low-hazard conditions. The model leverages spatial variation in fuels, potential fire behavior, tree density to locate optimal project areas and treatments within them. We tested the approach on a 245,000 ha dry forest landscape and analyzed how the process compares to local planning efforts. The study motivated the development of a broader framework of spatial fuel management strategies and a discussion of their respective ecological and management goals.

Methods

Study area

The Fort Rock portion of the combined Bend-Fort Rock Ranger District is located on the southeast portion of the Deschutes National Forest (Fig. 2), near Bend, Oregon. The area is a high priority for restoration activities and is currently delineated into 12 planning areas (Fig. 2). Dry forests dominated by ponderosa pine are most prevalent (70%), with lesser amounts of lodgepole pine (*P. contorta* var. *latifolia*, 20%), and mixed grand fir (*Abies grandis*) and Douglas-fir (10%).

Pre-settlement dry forests consisted primarily of open ponderosa pine stands with a relatively low density of large trees as determined by forest inventories and photos from early in the 19th century (Fitzgerald 2005). Stands were typically uneven-aged, with patches of regeneration resulting from fire and bark beetle disturbances (Fitzgerald 2005). The combination of logging and fire exclusion has transformed the forests into a mosaic of stand ages, density, and species composition. Many stands have a significant brush understory comprised of snowbrush ceanothus (*Ceanothus velutinus*) and antelope bitter brush (*Purshia tridentata*). A large portion of the study area consists of dense 80-year old ponderosa pine stands that contain high surface fuel loadings (>18 Mg ha^{-1}, Stanton and Hadley 2010) and are susceptible to stand replacement crown fires.

Fire frequency and severity has increased dramatically on the District and the surrounding Deschutes National Forest since the mid-1980s, with several large, stand replacing wildfires in recent years (Fig. 2). Fire history data obtained from the National Interagency Fire Management Integrated Database (NIFMID 2011) shows an average of about 60 ignitions per year (1985–2010) with 80% caused by lightning. About 10% of the study area has been burned by wildfire during 1985–2010, with 80% of the area burned by fires larger than 500 ha. The 10% of the study area that burned between 1985 and 2010 exhibited a mix of severity classes (22% high, 42% medium, 36% low) as derived from the Monitoring Trends in Burn Severity data (National Geospatial Data 2009). Annual area burned on the surrounding Deschutes National Forest has increased from about 0.28% per year over the period 1900–1999, to 1.2% between 2000 and 2010, a four-fold increase.

The long-term management goal for most of the study area is to restore a frequent, low intensity fire regime (planned and managed natural ignitions) as a means to control the accumulation of fuels and reduce the incidence

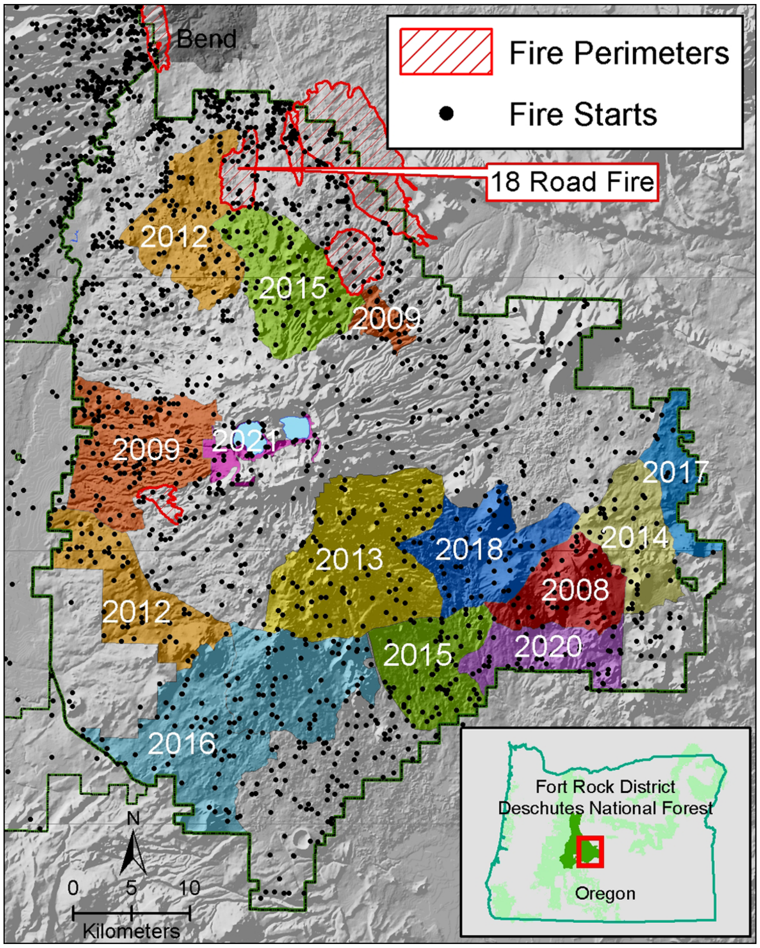


Fig. 2. Map of the study area showing past and proposed project area boundaries (solid colored polygons). Perimeters for recent (1990–2012) wildfires are red hatched polygons. Historical ignition points (1970–2010) are black dots.

of high-severity fires. Restoration treatments within the study area (Fig. 2) are implemented on 2000 to 8000 ha per year (average = 3000 ha between 2000 and 2012). The specific treatments mirror those elsewhere on dry forests in the western US (Agee and Skinner 2005, Roccaforte et al. 2008), where overstocked stands are thinned from below and surface fuels are treated to reduce potential wildfire behavior and protect mature ponderosa pine trees.

Quantifying restoration objectives

Although there are many important ecological goals in the management of dry forests (Allen et al. 2002), the presence of large, fire resilient ponderosa pine trees is widely used as an ecological indicator for sustainability of the dry forest ecosystem. We thus defined the management goal as protection of old growth ponderosa pine (PPOG) from potential wildfire loss. PPOG was defined as trees with a diameter >53.3 cm according to federal agency standards in the Pacific Northwest (Franklin et al. 1986). We mapped PPOG from the Forest inventory geodatabase that contained estimates of tree density, species and size for each of 16,632 stands (average size = 14.7 ha) within the study area. The geo-database is maintained by Forest Service staff and was developed using statistical imputation methods as described in Ager et al. (2007). The geo-database is used regularly on the Forests for forest wildfire modeling, project planning and related vegetation assessments.

Optimization approach

The optimization problem at hand is to locate a project area within the larger landscape (e.g., national forest district) and select stands for treatments to maximize the protection of PPOG from potential wildfire losses. Both the location of the project area and the treatment of individual stands can potentially contribute to the objective (PPOG). Specifically, the restoration objective value can be defined as

$$\mathrm{Max}\sum_{j=0}^{k}\left(Z_j N_j^T + (1 - Z_j)N_j^{NT}\right)$$

where Z is a vector of binary variables indicating which of the k stands are treated (e.g., $Z_j = 1$ for treated stands and 0 for untreated stands), N_j^T is the post-wildfire number of PPOG in stand j if treated, and N_j^{NT} is the post-wildfire number of PPOG in stand j if not treated. The solution has a spatial constraint because the collection of both treated and untreated stands in the project area needs to create a contiguous area within which the potential fire behavior is acceptable to managers for future use of landscape fire treatments (prescribed fire treatments and managed wildfire) to maintain fire-adapted conditions over time. Thus neither the treated nor untreated stands within the project can have a potential fire behavior that exceeds a management threshold, i.e., one that would prevent the liberal use of prescribed fire or trigger suppression activities during a wildfire being managed for restoration objectives. Spatial contagion of the low hazard condition creates a container within which free-burning wildfires and prescribed fires can be managed with a lower risk to managers, resulting in reduced suppression efforts over time, and increases in the use of fire to manage fuels. This constraint is important since risk from both prescribed and managed fires poses ongoing challenges to the expanded use of fire in restoration (Graham et al. 2012).

Although the model could have leveraged one of the many optimization algorithms used in forest planning (Baskent and Keles 2005), we favored a relatively simple algorithm and a two stage approach to permit wider application of the model by fuel planners. The problem was addressed with an algorithm that first searched for a contiguous set of stands that maximized predicted, post-wildfire PPOG, with the decision whether to treat the stands being pre-determined by whether the current potential fire behavior exceeded a threshold input by the user (Fig. 3). We used flame length as the treatment threshold (henceforth FL threshold) since it is a commonly used fire behavior metric in fuels planning. For each stand, the predicted, post-wildfire PPOG (henceforth *expected* PPOG) was estimated beforehand with the Forest Vegetation Simulator as described in the following section. The model required spatial data for each stand indicating (1) stand polygon centroid, (2) potential fire behavior as represented by flame length, (3) expected PPOG in the stand for both treated and untreated conditions, and (4) stand area (ha). The data were input into the model in an ArcGIS polygon shapefile. In addition to a treatment threshold, the user enters the total treatment allowance (area, ha) to represent an annual budget capacity for restoration treatments. Given the spatial input data, a FL threshold, and a treatment area constraint, the routine tested each stand as a seed location to create the project area, and added adjacent stands into the project while testing whether the stand required treatment (Fig. 3). Stands that had expected fire behavior that exceeded the FL threshold were treated, and the treatment area was incremented accordingly. Stands that did not require treatments were similarly absorbed into the project without penalty to the treatment area constraint. The objective value was incremented by the post-treatment, expected PPOG for stands that were treated, and the no treatment expected PPOG for those that were not. The priority for adding stands to the seed stand was based on the minimum distance between the candidate stand centroid and that of the seed stand, thus generating roughly circular project areas. As the project area expanded and additional stands were treated, the treatment area constraint was eventually met, and the project area was defined by the aggregate of treated and untreated stands. After all stands in the study area were tested as a potential seed location, the project area (set of stands) that resulted in the maximum expected PPOG was identified along with the objective value for the project (maximum expected PPOG)

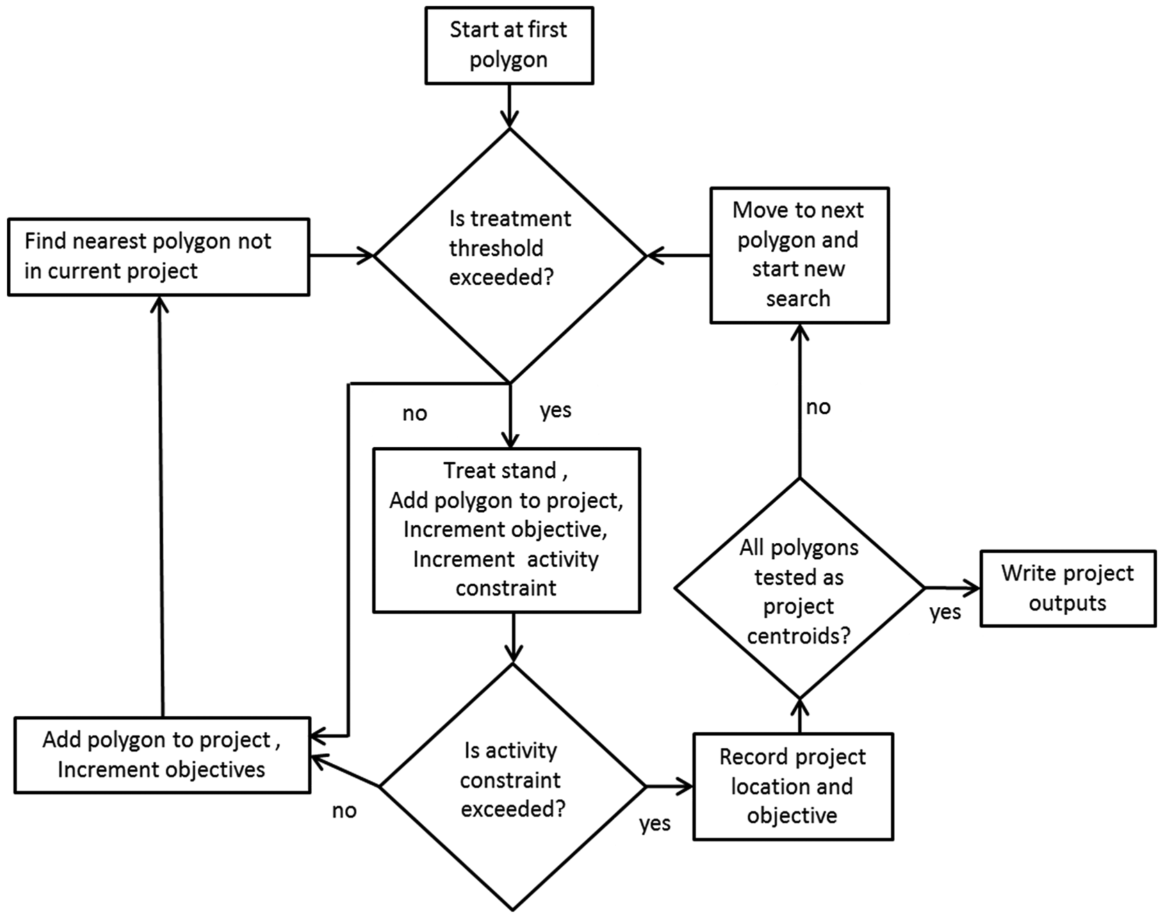


Fig. 3. Decision logic for the optimization model used to locate project areas. The algorithm tests each stand as the seed location for a project, and absorbs adjacent stands until a total area treated constraint is met. Stands that exceed a predetermined fire behavior threshold require treatment. The model identifies the aggregate of polygons that maximize the restoration objective and the polygons that require treatment. In the current study, polygons were defined as stands, treatment thresholds were measured by potential flame length, activity constraint was the total treatment allowance, and restoration objective was the total predicted post-wildfire, old growth ponderosa pine in the project area.

and the specific stands that required treatment.

Next, we used the model to examine how the maximum expected PPOG and the optimal project location changed in response to (1) different investment levels, using area treated as a surrogate for an annual budget; and (2) treatment intensity, as represented by the FL threshold. These two variables have counteracting effects since increasing area treated can result in larger projects and potentially more PPOG, whereas increasing the FL threshold reduces the frequency of treatments within a project and thus more PPOG are susceptible to wildfire mortality. This sensitivity analysis consisted of 300 simulations using a FL threshold between 0.5 and 15 m (step = 0.5 m), and a treatment area between 300 and 3000 ha (step = 300 ha).

To better understand how expected PPOG was affected by the above treatment parameters, we post-processed outputs from the simulations to partition the expected PPOG into two components: (1) the total PPOG in the project that was conserved from wildfire by treatments, and (2) the total PPOG that was lost due to wildfire mortality. We then calculated a net PPOG as the difference between the two to derive a variable

Table 1. Scheduling of fuel treatments and wildfire simulations to quantify the potential benefits of fuel treatment to reduce wildfire impacts on old growth ponderosa pine.

Simulation year	Treatment	No treatment	Description†
1	Thinning	NA	Retention of large fire resilient trees
2	Surface fuel removal	NA	90% of surface fuel (2.5–30.5 cm) removed
3	Underburn	NA	Conditions in Table 2
4	Wildfire	Wildfire	97th percentile August weather and fuel moistures based on 22 years of local weather station data

Notes: The activities represent a typical fuel treatment sequence within the study area to reduce wildfire behavior and potential mortality to old growth cohorts. All 16,632 stands in the project area were simulated with and without treatments and then exposed to a wildfire simulation to calculate potential mortality to ponderosa pine old growth. Inventory data represented year 2010 conditions in the study area.

†See also text.

that measured the net effect of the wildfire and treatments on total PPOG.

To demonstrate how the model could be used to develop a long-term restoration plan composed of multiple projects over time and space, we ran the model in a recursive process where each successive run considered only the portion of the project area that had not been assigned to a project area in a previous run. We performed two simulations using a treatment area constraint of either 3000 or 7000 ha, and a FL threshold of 4 m. The treatment area represented the minimum and average area (respectively) in recent restoration and fuel management projects. The FL threshold was chosen based on initial simulations that showed a 4 m threshold resulted in treatment densities (percent of area treated within a project) that resembled operational values on the Deschutes NF. The outputs were also used to examine how expected PPOG changed from the highest (selected first) to lowest (selected last) priority project area to understand the potential value of locating optimal projects within the larger study area.

To facilitate the simulations, we developed the Landscape Treatment Designer (Ager et al. 2012*a*), a standalone desktop program that can analyze landscape treatment options for a wide range of fuel management objectives, including the dry forest restoration problem described here. The program has an option to batch process many simulations for a range of input parameters, thereby automating the sensitivity analyses described above.

Assessing current fire behavior and the effect of treatments

To quantify current fire behavior for each stand, as well as the effect of fuel treatments on expected PPOG, we used the Forest Vegetation Simulator and the Fire and Fuels Extension (FVS-FFE, Rebain 2010). The FVS-FFE modeling system has been used in numerous studies to examine stand-scale fire and fuel dynamics (Johnson et al. 2011). FVS-FFE and the limitations of fire models in particular are described elsewhere (Cruz and Alexander 2010). We simulated 'treatment' and 'no treatment' scenarios followed by a wildfire for each stand to calculate the potential effect of treatments on improving fire resiliency of PPOG. The fuel treatments closely paralleled procedures used on the Deschutes NF (Table 1) and in previous simulation studies (Ager et al. 2007) and favored the retention of PPOG, and large trees in general, with the goal of reducing surface, ladder, and canopy fuels that contribute to severe fire behavior and PPOG mortality. We used a thinning efficiency of 90% to retain understory cohorts for future old growth recruitment. After thinning we modeled site removal of 90% of the surface fuel between 2.5 and 30.5 cm followed by an underburn. The conditions for the latter were adopted from fuel management projects within the study area and previous studies (Ager et al. 2007), and assumed a 6.4 km hr^{-1} wind-speed, 21.1°C air temperature, and fuel moistures as specified in Table 2. Both the untreated and treated stands were subjected to a wildfire using FVS-FFE keyword SIMFIRE and weather conditions from a 22 year record of data from the Lava Butte remote automated weather station located within the

Table 2. Fuel moisture values (%) for simulated underburns and wildfires.

	Fuel class†						
Activity	1-h	10-h	100-h	1000-h	Duff	Live woody	Live herb
Wildfire	2	3	5	6	15	60	30
Underburn	12	13	14	15	125	120	90

Notes: Wildfire parameters derived from a 22 year record (1987–2010) for the peak fire period (August) from the Lava Butte remote automated weather station located within the study area. Underburn fuel moistures were provided by fuels staff on the District based on their field measurements during recent burn projects.

†See text for sources of the parameter values.

study area (Tables 1 and 2). The wildfire scenario represented 97th percentile conditions during August, which corresponds to historical peak fire season. Wildfires assumed 40 km hr^{-1} windspeed and 33.9°C air temperature, and fuel moistures as specified in Table 2. The simulation parameters were similar to conditions during recent wildfires within (18 Road Fire, Fig. 2) and adjacent to (Davis Fire) the study area (Ager et al. 2007). The post-fire tree mortality, as predicted by FVS-FFE in the year following the wildfire, was then used in the optimization modeling as described below. Tree mortality in FVS-FFE is modeled as a function of scorch height, crown length, diameter at breast height (DBH), and species-dependent bark thickness as developed from empirical studies (Ryan and Reinhardt 1988, Ryan and Amman 1994, Rebain 2010). The same mortality algorithms are used in several other fire modeling systems including First Order Fire Effects Model (FOFEM, Reinhardt et al. 1997) and Behave Plus (Andrews 2007).

Results

Maps of flame length (FL) from simulated fires for untreated stands suggested substantial spatial variation in fire behavior within the study area, with FLs exceeding 5 m in stands having the highest concentration of PPOG (Fig. 4A, B). The highest FL from simulated wildfire was observed for mixed conifer stands in the higher elevation portions of the study area on the flanks of Paulina Peak (center of study area), although pockets of high FL were observed in many other stands. Modeled fire behavior indicated that much of the area, if untreated, would burn with either torching (57%) versus surface (30%) or active crown fire (13%). The effect of simulated fire on PPOG mortality was highly variable in untreated stands with FLs of less than 4 m (Fig. 5). The mean FL for untreated conditions was 8.6 m, and resulted in dramatic reductions in PPOG (Fig. 4A, C). By contrast, stands where treatments were modeled had FLs from simulated fires averaging about 0.5 m, and little reduction in PPOG (Fig. 4A, D) although both results generally reflected the spatial variation in the density of the species (Fig. 4).

Simulation results for a range of treatment area constraints and FL thresholds are shown in Fig. 6. Each data point represents one simulation where a project area was located such that expected PPOG was maximized given a FL threshold and treatment area constraint. Note that both treated and untreated stands contribute PPOG to the expected PPOG value. That is, the expected PPOG for a project area accounts for post-wildfire PPOG in both treated and untreated stands. As expected, PPOG within the project increased with allowable treatment area (Fig. 6B), although the rate of increase was dependent on the FL threshold. At the lowest FL threshold (0.5 m) all stands required treatments (expected fire behavior exceeded the FL threshold) and thus the area within the optimum project equaled the treatment area (Fig. 6A). FL thresholds greater than 8 m resulted in relatively large project areas (Fig. 6A), because few stands exceeded the FL threshold and required treatment (Fig. 6D). Thus, larger project areas can be created by either raising the treatment allowance (i.e., larger budget) or the FL threshold (Fig. 6A). At a given FL threshold, the larger project areas contain more PPOG by virtue of their size, as shown by the optimization model (Fig. 6B).

We examined the effect of FL threshold and treatment area constraint on the proportion of the project area treated (Fig. 6D). Interestingly, we observed instances in which increasing the treatment area constraint also resulted in a higher

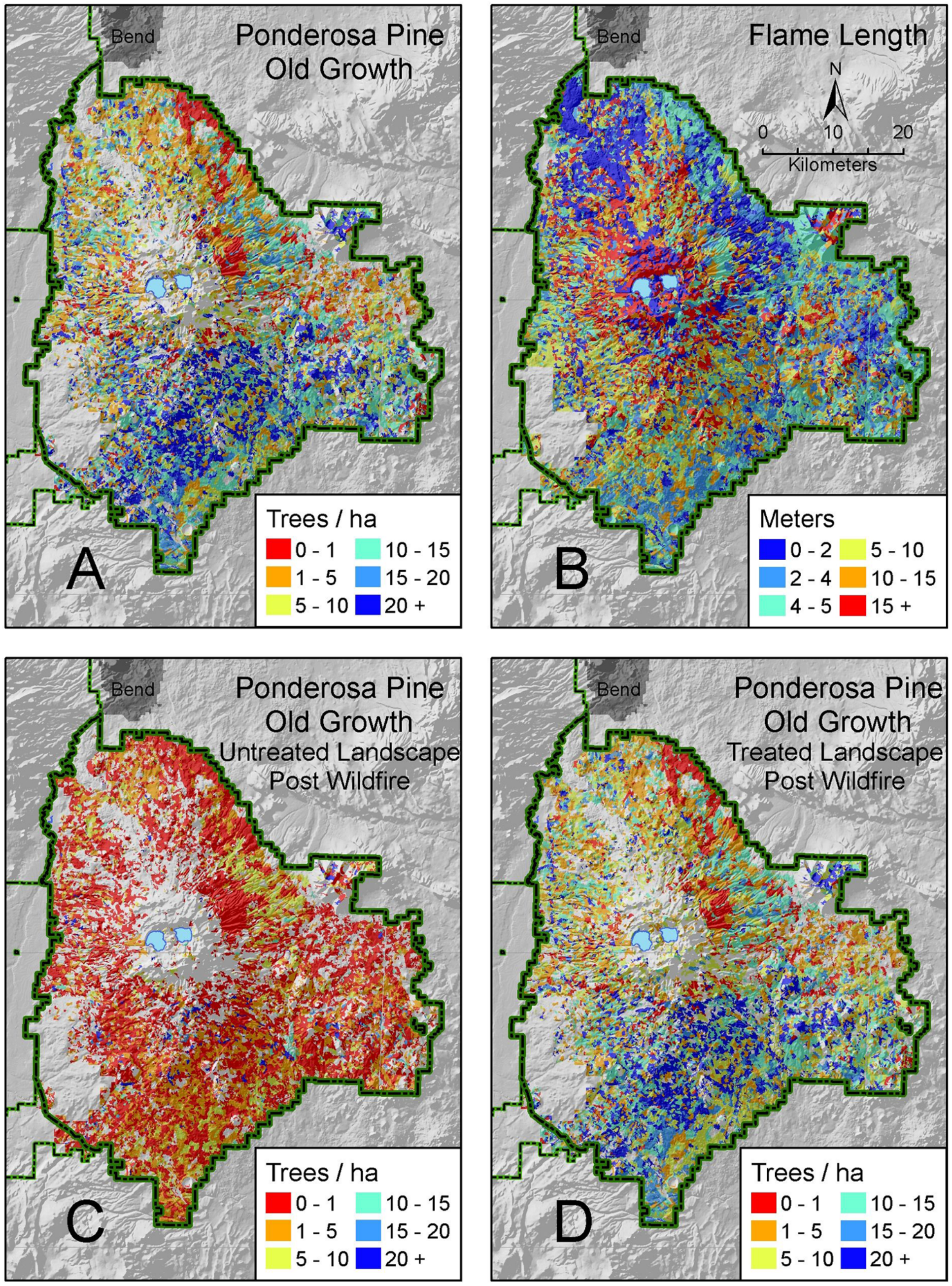


Fig. 4. Maps showing modeled outputs: (A) Predicted tree density of ponderosa pine old growth (PPOG), (B) potential flame length from a modeled wildfire (untreated), (C) predicted PPOG after a wildfire (untreated), and (D) predicted PPOG after treatment and wildfire. Wildfire weather conditions assume 97th percentile conditions as determined from local weather data.

proportion of treated area (Fig. 6D), apparently because stands that contributed expected PPOG without a treatment (e.g., had previously been treated) were localized within the study area, and as the treatment area constraint was increased, these stands became scarce, thus requiring more stands to be treated as the project expanded.

The above results showed restoration design

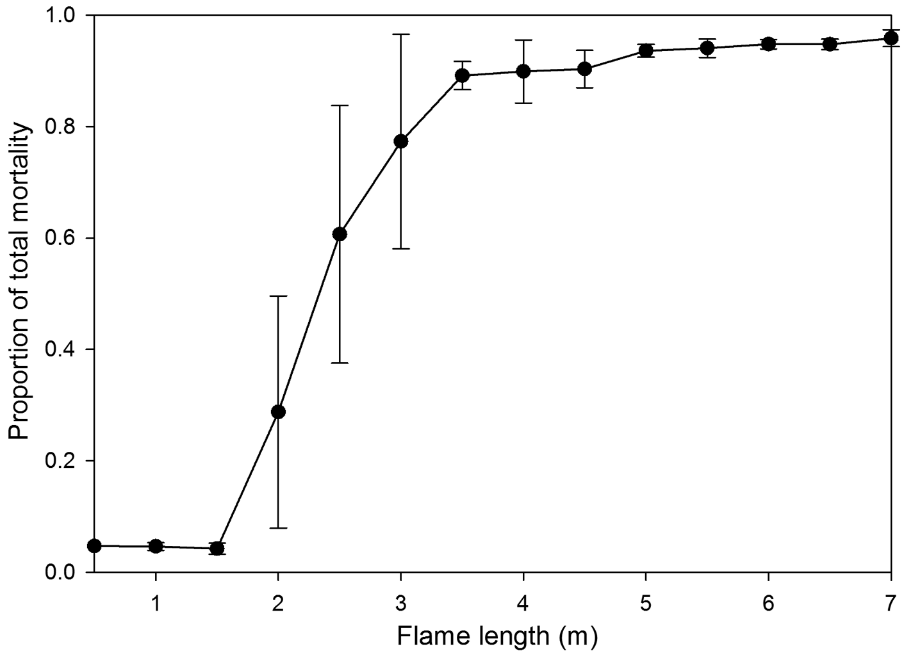


Fig. 5. Mortality of old growth ponderosa pine as a function of flame length for modeled fire behavior in untreated stands. Data obtained from simulations of the 16,632 stands in the study area using conditions described in the text. Bars are standard deviation for 0.5 m flame length intervals.

tradeoffs between treatment area constraint, FL threshold, and expected PPOG. Specifically, conserving the largest population of PPOG can be achieved with either a low or high FL threshold, the former creating small project areas with high resilience to fire, the latter creating large project areas that can contain more PPOG by virtue of their size, but leave PPOG vulnerable to fire mortality. The tradeoff between these divergent restoration strategies was quantified by partitioning the expected PPOG into that conserved by treatments versus lost by not treating, and calculating the difference to yield a net PPOG. Thus, if larger projects maximize expected PPOG by sacrificing a proportion of trees to wildfire, a decrease in the net value will be reflected. The results (Fig. 6C) showed that for scenarios where the FL threshold was relatively low (<4 m), and most stands required treatment (exceeded the threshold), the net PPOG increased rapidly with increasing treatment area constraint. At high treatment FL thresholds (>8 m), the net PPOG became negative, showing that the loss of PPOG in untreated stands was significant on a relative basis. At intermediate FL threshold values (5–7 m), the optimization model located projects and treatments within the project area, and generated a positive net PPOG, but only when the treatment area allowance was less than 1500–2100 ha. The latter resulted from the fact that within the study area there are some localized conditions where PPOG density is high and predicted mortality is low even at a relativly high flame lengh.

The locations of the optimal project areas identified in the simulations were mostly located in either the northeast or the south central part of the study area (Fig. 7). However, these particular project areas represented divergent restoration strategies, where the northern location was optimal for higher FL thresholds (6.5 m), and the southern was optimal for a lower (3 m) FL threshold.

To apply the model to prioritize projects for a long-term restoration plan for the study area, we recursively executed the optimization model, resulting in a sequence of project areas and respective priorities (Fig. 8). The simulations were performed for treatment constraints of both 3000 ha (Fig. 8A) and 7000 ha (Fig. 8B) with a 4 m

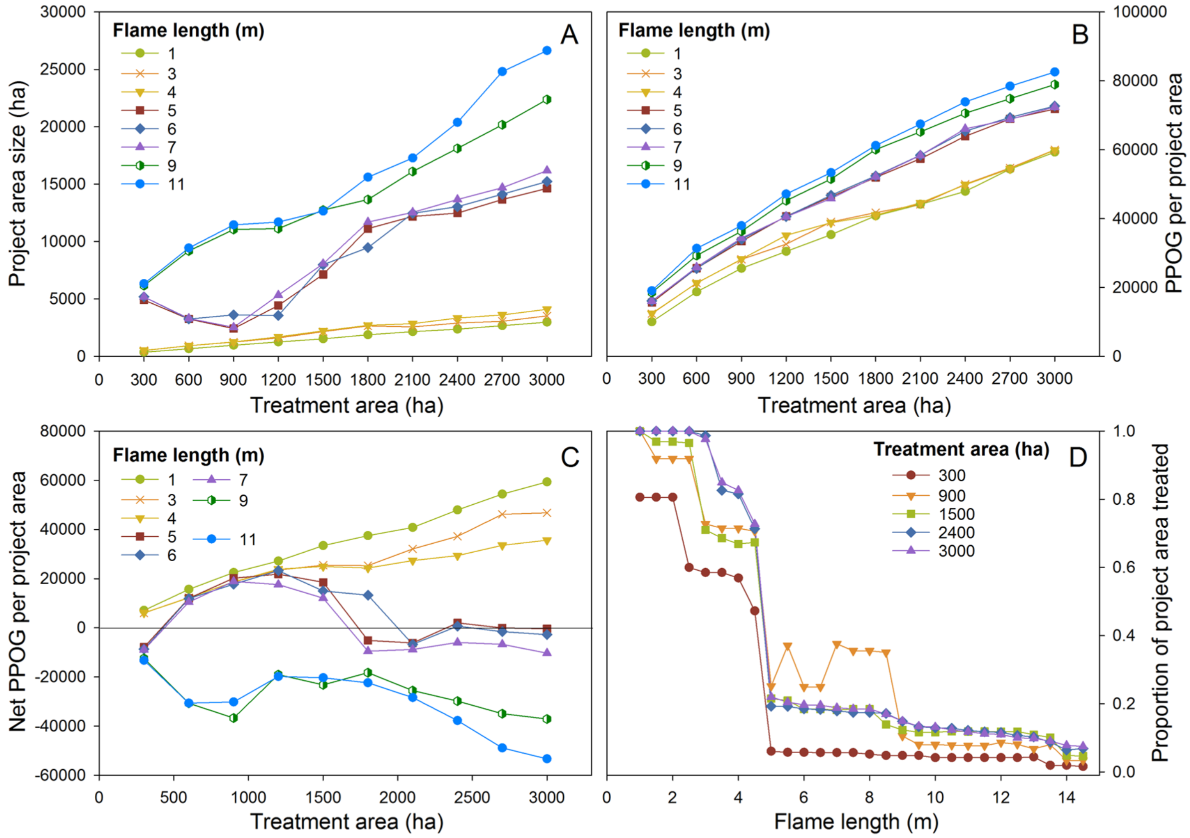


Fig. 6. Outputs from the optimization model under different combinations of flame length (FL) threshold and treatment area constraint. (A) Project area size; (B) ponderosa pine old growth (PPOG) per project; (C) net PPOG per project area calculated as the difference between the PPOG in treated stands minus the PPOG mortality in untreated stands, post wildfire; and (D) proportion of project area treated.

FL threshold. The lower treatment allowance generated 24 projects with an average size of 5,800 ha (Fig. 8A), while the latter allowance identified nine projects with an average size of 15,100 ha (Fig. 8B). Expected PPOG showed a steep decline as projects were added to the study area (Fig. 9) with the rate of decline substantially larger for the 7000 ha treatment constraint compared to 3000 ha. The rate of decline indirectly supported the idea that tradeoffs exist in terms of locating and sequencing project areas within the larger study area, and particular locations and respective treatments represent optimal solutions to the problem.

Discussion

Meeting the long-term goals of dry forest restoration will require dramatic increases in prescribed and managed fire that burn under conditions that pose minimal ecological and social risk. Optimization models can facilitate the attainment of these goals by prioritizing management activities and identifying investment tradeoffs (Christensen and Walters 2004). In this study, we developed and tested a model for prioritizing dry forest restoration efforts that are underway on national forests throughout much of the western US (USDA-USDI 2001, Noss et al. 2006*b*). The model provides a quantitative and spatial framework to help understand the performance of dry forest restoration that has been lacking in previous discussions (Noss et al. 2006*a*, Noss et al. 2006*b*) and in implementation of restoration strategies within federal land management agencies (USDA-USDI 2001). The

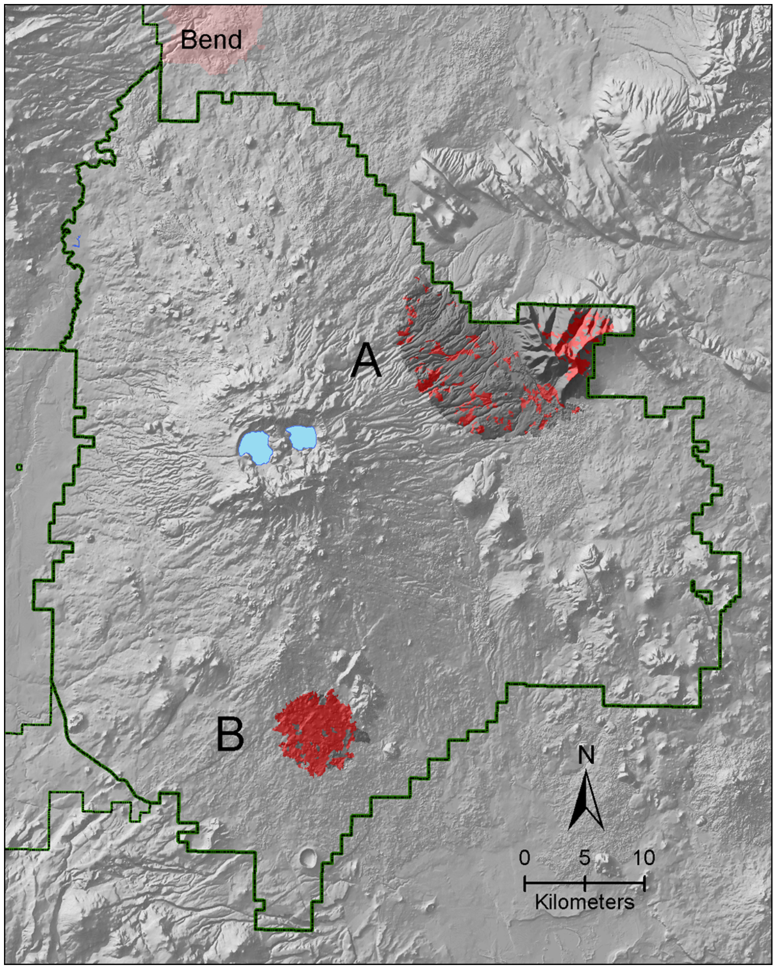


Fig. 7. Project areas and suggested treatment locations for two model simulations. The northern project area resulted from optimizing expected PPOG for a 6.5 m flame length threshold and 3000 ha treatment allowance, while the southern project area resulted from a 3 m flame length threshold and the same treatment allowance. Areas shaded in red were selected for treatment based on the expected flame length exceeding the threshold established in the simulation. Areas in dark gray are within the project areas but were not selected for treatment.

broad goal of the model is to optimize the location of projects to facilitate the efficient future use of prescribed and natural fire as a means to sustain fire resilient forests and reduce the likelihood of uncharacteristic fire and associated ecological loss. The sensitivity analyses in particular identified the tradeoffs associated with particular treatment strategies in terms of total project area versus level of post-treatment wildfire hazard. The prioritization approach leverages the effect of past management, wildfires and other disturbances that have created a heterogeneous mosaic of conditions with respect to ecological values and wildfire risk. We note that the methods and model can be applied throughout the dry forest ecosystems in the western US using input from existing data (Rollins 2009, Drury and Herynk 2011) and models (Andrews et al. 2007, Ager et al. 2012*a*) to examine tradeoffs among different restoration strategies.

Data from recent restoration projects on the Deschutes NF provide an interesting comparison with the modeling outputs. Historically (2000–2012), restoration projects (including treated and untreated area) within and adjacent to the study area had a mean size of nearly 9000 ha (range

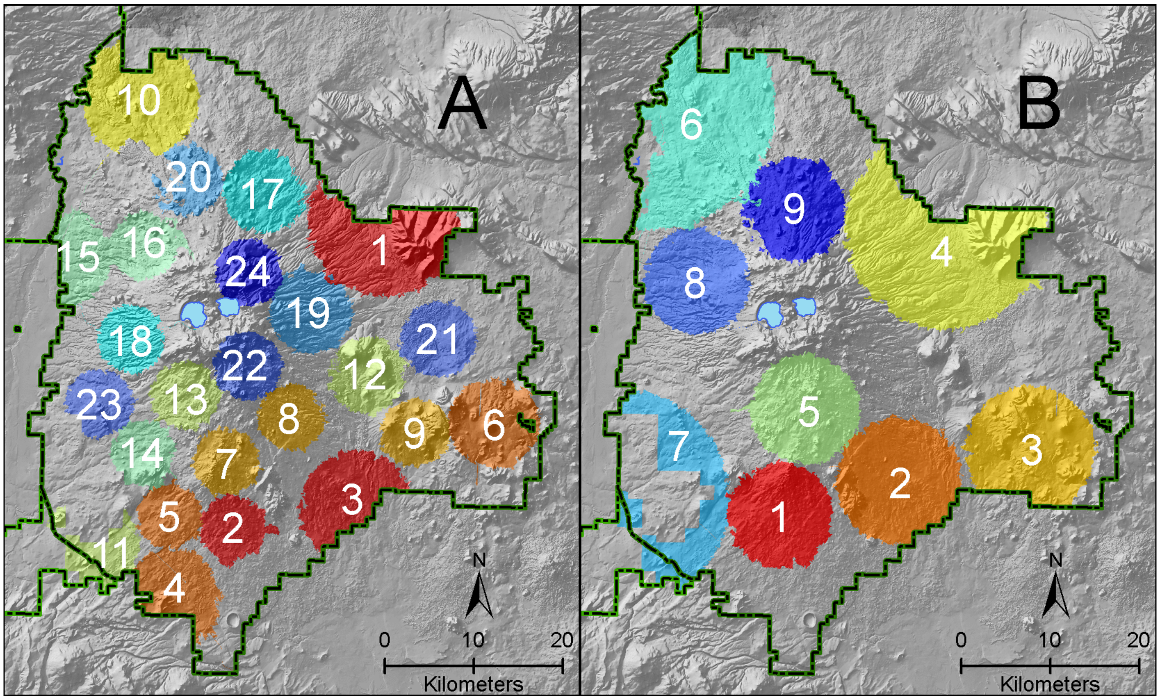


Fig. 8. Results of recursive simulations to prioritize the entire study area into a sequence of project areas. Ranked projects with (A) 3000 ha treatment allowance and 4 m flame length (FL) threshold, and (B) 7000 ha treatment allowance and 4 m FL threshold. The maps show the ranking of projects in terms of maximizing objectives subject to treatment area constraints and FL thresholds. The model cycles through the landscape until insufficient area exists to build additional projects.

3000–22000) and treated about 35% (3000 ha) of the area (Fig. 2). This treatment proportion roughly corresponds to a flame length threshold of about 4 m (from Fig. 6D) and PPOG conserved through treatments exceeding the loss in the untreated stands (Fig. 6C). A lower FL threshold would result in a marginal gain in net PPOG (Fig. 6C), a smaller project area, and a longer restoration rotation for the study area. Although a higher FL threshold would create a larger project area, a subsequent wildfire would result in a net loss of PPOG after wildfire (e.g., Fig. 6C, 9 m flame length).

The key tradeoff associated with dry forest restoration concerns the balance between the scale of restoration and the level of fire resiliency. Under a fixed budget (treatment area constraint) creating high fire resiliency reduces the size of the restored area, and thus leaves the larger landscape at risk. Relaxing the treatment threshold results in a larger restored area and potentially allows accelerated use of managed fire, but also leaves more risk of loss within the project area. In our study, increasing treatment intensity reduced the potential loss of PPOG to wildfire within projects, but it also reduced the size of the restored area, thus prolonging the time to restore the larger landscape and increasing the chance for wildfire losses outside of the project. Although the optimal strategy is dependent on the location of highly uncertain extreme fire events, we argue that the optimal approach over the long run will be the one that best accelerates the use of managed and natural fire within areas of highest ecological value.

The existing restoration prioritization system used by federal land management agencies employs a fire regime-condition class rating, and prioritizes stand management based on the departure from HRV (Hann and Strohm 2003, Holsinger et al. 2006). The system potentially ignores the contagion of fire hazard on the surrounding landscape, thereby defeating the broad goal to re-introduce fire to maintain fuel

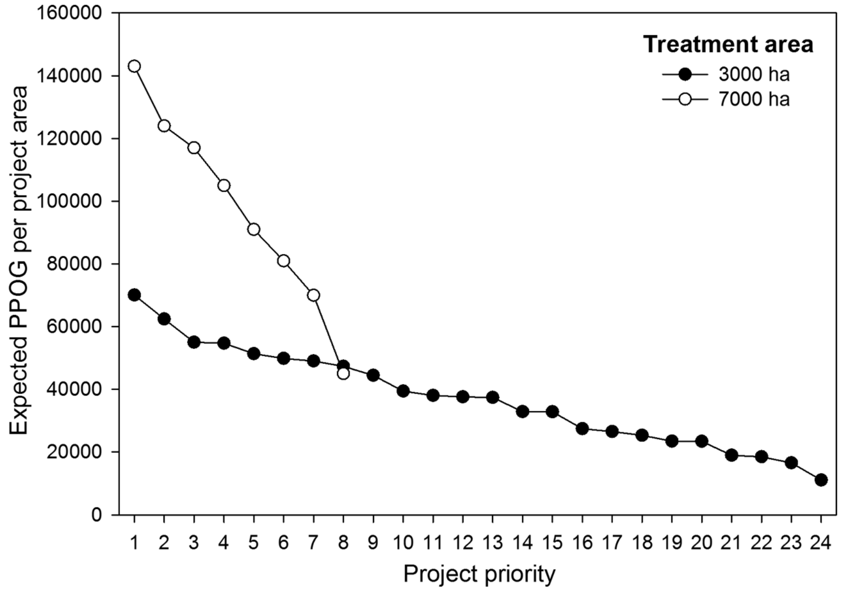


Fig. 9. Expected ponderosa pine old growth (PPOG) per project area for the two simulations shown in Fig. 8. Project priority refers to the restoration priority, as determined by iteratively executing the optimization process and removing the optimum project areas from consideration. Project priority values correspond to Fig. 8.

loadings and resilient stand structures. Moreover, a high departure from HRV can result from factors other than fuel loadings, such as a change in species composition (Keane et al. 2007), and thus a high departure does not necessarily translate to high fire risk or hazard (Franklin and Agee 2003).

Our modeling employed a relatively simple spatial algorithm compared to other systems developed for landscape optimization in forest ecology that have employed mathematical optimization methods (Hof and Bevers 2002, Baskent and Keles 2005). The disadvantage of our model is that it does not test every possible spatial arrangement of stands to locate project areas, nor does it search for optimal combinations of treatment types and spatial arrangements. However, our goal was to provide a broad decision support tool to planners, and the computational and software requirements of mathematical programming would preclude application in the field. The software we developed as part of this study (Ager et al. 2012*a*) solves large landscape problems (e.g., 10^6 ha) in minutes and is easily adopted by field units for local planning on national forests.

Another decision that simplified the modeling was to estimate wildfire impacts on old growth ponderosa pine using stand- versus landscape-scale fire modeling. In the former we assume: (1) each stand burns independently without consideration of the fire behavior in adjacent stands, (2) a heading (versus backing or flanking) fire direction, and (3) equal probability of wildfire. Landscape fire modeling can be used to simulate thousands of wildfires and estimate burn probabilities thereby allowing the calculation of expected loss (risk) to old growth and other ecological values (Ager et al. 2007, 2010). We experimented with this approach and found little benefit despite substantial added complexity. Most stands in a severe wildfire burn as a heading fire since this is the maximum direction of spread, and most of the annual area burned by wildfire is from severe fires. Secondly, the average stand size in the study area is nearly 15 ha, sufficiently large to buffer fire behavior from adjacent stands. Lastly, while our landscape fire modeling from previous work suggested spatial variation in burn probabilities within the study area (Ager et al. 2012*b*), the variation in likelihood (0.1–1%) was relatively minor compared to that associated with the density of old growth ponderosa pine (0–108 trees ha^{-1}) and potential wildfire mortality in the stand (0–100%), and thus the latter two variables drive the solution compared to the former.

The existing literature on spatial planning and optimization for forest management (Baskent and Keles 2005) has not addressed fire restoration issues. Prior studies on spatial prioritization of fuel management have primarily concerned optimizing the arrangement of treatments to disrupt fire spread and protect areas from burning, rather than restoration of fire as a natural process (Bevers et al. 2004, Finney et al. 2007, Lehmkuhl et al. 2007, Parisien et al. 2007, Wei et al. 2008, Kim et al. 2009, Konoshima et al. 2010, González-Olabarria and Pukkala 2011). For instance, the treatment optimization model in FlamMap (Finney 2007) allocates treatments to block the fastest wildfire flow path and optimizes the dimensions of the individual treatment units so that the time to burn through the unit equals the time to burn around it. The focus on wildfire likelihood (i.e., spread rate) in this and other studies was motivated by the fact that most of the area burned and resulting damage are from relatively few large fires that spread over large distances (FAO 2007), and retarding spread increases containment success (Finney et al. 2009). However, attempts by field units to apply this spatial optimization tool as part of dry forest restoration efforts have been problematic (A. A. Ager, *personal observation*), partly because it is difficult to demonstrate dramatic reductions in the rate of spread and burn probability from restoration treatments (Reinhardt et al. 2008). Previous work on decision support systems specifically for forest restoration is limited. Several studies have created spatial prioritization systems by combining a number of ecological and operational data into GIS overlays (Hiers et al. 2003, Sisk et al. 2006). The system developed for the national fire plan's prioritization system (Keane et al. 2007) derived HRV departure indices that could be used to prioritize restoration activities. None of the above studies attempted to spatially optimize the location of treatments or quantify the tradeoffs associated with specific treatment schedules and parameters.

One concern with dry forest restoration programs is that creating low hazard landscapes might promote the homogenization of dry forests and remove structural and biotic diversity (Allen et al. 2002). However, variation in fuel treatment activities and prescribed fire behavior can retain and create spatial variation in structure within project areas by adherence to specific prescription guidelines (Larson and Churchill 2012). Variation in fuels, topography, regeneration patterns, and fire weather all promote structural mosaics on both treated and untreated landscapes under natural fire regimes. It is the contagion of high hazard forest structure (i.e., lack of variation) that evolved over the last century that has contributed to uncharacteristic fire regimes in dry forests, and increasing rather than reducing spatial variation in structure will remain an important goal.

It is useful to interpret the current study in the broader context of fuel management and fuel treatment optimization approaches on public lands (Finney et al. 2007, Reinhardt et al. 2008, Collins et al. 2010). Whereas stand management strategies such as thinning and prescribed fire are widely accepted as effective means to reduce the impacts of surface and crown fire in dry pine forests (Roccaforte et al. 2008, Safford et al. 2012), an ordination of different landscape strategies along the continuum between fire restoration and exclusion has been lacking. The choice of the most appropriate landscape fuel management strategy is determined by specific combinations of: (1) spatial patterns of human and ecological value, (2) fire management goals, (3) fire ecology, and (4) wildfire exposure as measured by likelihood and intensity (Fig. 10). Collectively, these factors determine the extent to which long-term risk management emphasizes restoring natural fire regimes versus protecting highly valued resources with suppression, and the most appropriate spatial fuel management strategy (bottom, Fig. 10). Developing robust fuel management strategies where steep gradients exist for the above factors (e.g., wilderness adjacent to an urban interface) will be a challenge. Landscape fuel management tools (Ager et al. 2012*a*) can facilitate the development of these strategies.

There remain many challenges to achieve forest restoration goals, especially considering the highly stochastic occurrence and behavior of wildfires that threaten large areas of dry forests that are currently at risk for uncharacteristic fire. Encroaching urban interface, smoke, budget

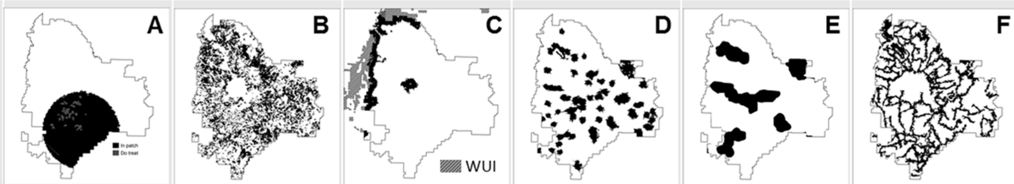
Spatial Strategies for Fuel Management						
	Restoration of low severity fire regime	**Broad landscape protection**	**Localized protection**	**Protection of dispersed values**	**Restoration of mixed severity fire regime**	**Strategic containment**
Spatial pattern of values	High density, dispersed	Low density, dispersed	Variable density, clumpy	Clumpy	Any	Low or none
Landscape goal	Low hazard fire containers	Disrupt spread, facilitate containment	Localized defensible fuel breaks	Dispersed defensible fuel breaks	Restoration of dispersed natural fire barriers	Contain large fires at defensible locations
Performance measure	Area burned by prescribed and natural fire	Reduction in landscape burn probability	Local reduction in exposure near values at risk	Reduced exposure to fire	Landscape reduction in hazard and burn probability	Area burned by natural fire
Treatment goal	Reduce fire severity	Reduce fire spread rate	Facilitate suppression	Facilitate suppression	Reduce fire spread rate	Facilitate suppression
Example map						

Fig. 10. Spatial framework for landscape fuel management. Strategies are determined by fire regime, fire management objectives, and the spatial pattern of values at risk. Black shaded areas in the maps depict fuel treatment areas within the example landscape. (A) Low hazard fire containers for dry forest restoration, (B) protection of dispersed values using the approach of Finney (2007) where treatments are arranged to maximize the reduction in spread rate, (C) defensible fuel breaks around a wildland urban interface (WUI), (D) defensible fuel breaks around dispersed values (e.g., critical wildlife habitat), (E) restoration of natural fire barriers (e.g., hardwood forest in a conifer matrix), and (F) high hazard fire containers surrounded by networks of defensible fuel breaks.

constraints, and a growing wildfire risk problem all contribute to the difficulty of restoring fire adapted dry forests while meeting demands for ecosystem services on national forests. Landscape decision support tools to prioritize restoration management will likely play an increasingly important role in the development of restoration programs and contribute to the goal of returning natural variability and resilience to fire-frequent forests in the western US.

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