Hazardous Fuel Treatments, Suppression Cost Impacts, and Risk Mitigation[1]

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Abstract

Land management agencies face uncertain tradeoffs regarding investments in preparedness and fuels management versus future suppression costs and impacts to valued resources and assets. Prospective evaluation of fuel treatments allows for comparison of alternative treatment strategies in terms of socioeconomic and ecological impacts, and can facilitate tradeoff analysis. This presentation will demonstrate recently developed methodologies for estimating potential suppression cost impacts of fuel treatments. The approach pairs wildfire simulation outputs with a regression cost model, estimating the influence of fuel treatments on distributions of wildfire size and suppression cost. A case study focuses on a landscape within the Deschutes National Forest in central Oregon, USA, and results suggest substantial treatment effects. An auxiliary analysis demonstrates the impacts of fuel treatments in terms of reduced exposure of values at risk, to quantify the broader potential benefits of fuel treatments. Effectiveness of treatments in the case study is contingent on large-scale implementation of fuel treatments across the landscape, and sufficient maintenance to ensure treatment effectiveness over the duration of the analysis period. Future applications and integration with other modeling approaches will be highlighted.

Key Words: exposure analysis, hazardous fuels, risk assessment, suppression cost

Introduction

The U.S. Forest Service (USFS) and other public land management agencies spend considerable amounts of money managing wildland fires every year, to the

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point where a busy fire season can threaten the ability of agencies to meet non-fire needs and maintain forest health (Thompson and others 2013a). Yet wildland fires continue to cause significant damage to forest ecosystems and the built environment. While investments in suppression responses may help protect valuable resources from the damaging effects of fire, suppression is costly and also puts firefighters in harm's way.

Investments in fuels management hold promise for reducing potential costs and damages of wildland fire by reducing the size and intensity of future fires (Ager and others 2010, Moghaddas and others 2010). But managers face uncertain tradeoffs over the potential effects of fuel treatments, including reduced future suppression costs (and risks to firefighters involved in suppression), damage to ecological values, and damage to homes and other structures in the wildland-urban interface (WUI). That is, the payoffs of an investment in fuel treatments are not well known in advance, which makes it difficult to design and implement an efficient fuels treatment program.

In this paper we illustrate a method for assessing the potential effects of a fuel treatment project, and demonstrate its use on a case-study landscape in the Deschutes National Forest in the United States. We build on previous efforts to model how fuel treatments affect the growth, size, and costs of future fires (Thompson and others 2013b) by interacting simulated fire perimeters with the geographic distribution of highly valued resources and assets (HVRAs) that are exposed to fire. This analysis can be used to describe the likely effectiveness of fuel treatments in reducing the exposure of HVRAs to the damaging effects of fire, and as a means of comparison between different proposed fuel treatment options.

Assessing Fuel Treatment Effectiveness

The primary purpose of this paper is to examine how a landscape-scale fuel treatment program is likely to change future fire outcomes. At the heart of this assessment is a comparison of likely fire outcomes under existing fuel conditions (EC) and post-treatment (PT) fuel conditions. Formally, we use the simulations to calculate an expected treatment effect as the change in expected fire outcomes:

$$\Delta E(Z) = E(Z_{PT}) - E(Z_{EC}), \qquad (1)$$

where Z is a vector of k measures of fire outcomes, $Z = \{Z_1, Z_2, \ldots, Z_k\}$. The treatment effect $\Delta E(Z)$ represents the difference in outcomes for the average fire[1]. For the case study in this paper, Z is comprised of suppression costs (C), area burned

[1] In this case study we explicitly specify that fuel treatments do not affect the number of ignitions, and we do not model differential initial attack efforts. Treatment effects may indicate fewer escaped, "large" fires on the basis of reduced rate of spread and increased containment likelihood. The effects of these fires on HVRAs may still be modeled, but suppression costs cannot be estimated for these smaller fires.

in the wildland-urban interface (WUI), area burned in threatened and endangered species habitat (TE), and area burned in old-growth forest stands (OG)[2].

The simulation method described in the next section, combined with calculations of suppression costs and HVRA exposure, generates distributions of fire outcomes under existing and post-treatment fuel conditions. That is, each element of *Z* is associated with a simulated distribution under each condition:

$$\text{EC:} \quad f^{EC}(Z_k) \sim \left(\mu_k^{EC}, \sigma_k^{EC}\right) \tag{2}$$

$$\text{PT:} \quad f^{PT}(Z_k) \sim \left(\mu_k^{PT}, \sigma_k^{PT}\right) \tag{3}$$

Estimated expected outcomes under EC and PT ($\hat{\mu}_k^{EC}$ and $\hat{\mu}_k^{PT}$) are the mean value of the simulated distribution of each element of Z. Standard errors used to calculate confidence intervals for $\hat{\mu}_k^{EC}$ and $\hat{\mu}_k^{PT}$ are generated via bootstrapping (Efron 1979).

Estimates of $\hat{\mu}_k^{EC}$ and $\hat{\mu}_k^{PT}$ can be interpreted as the expected marginal effect of fire on the untreated and treated landscape, respectively. The expected treatment effect, *ΔE(Z)*, is the difference in marginal effects due to fuel treatments. Thus,

$$\Delta E(Z_k) = \mu_k^{EC} - \mu_k^{PT} \quad \forall k. \tag{4}$$

Methods

The evaluation of potential treatment effects involves first modeling how treatments will impact fire behavior, and, in turn, modeling how altered fire behavior may impact suppression costs and exposure of HVRAs to fire.

Wildland Fire Simulation Modeling

The results in this paper are based on simulations of fires before and after a fuel treatment has been applied to the landscape. We compare potential changes in fire sizes by altering the surface fuel models and canopy variables resulting from treatment. This approach explicitly seeks to capture both on-site and off-site effects of fuel treatments, which is especially important in areas like the western U.S. where the predominant source of burn probability is large fire spread from remote ignitions.

Fires are simulated using the large fire simulation model, FSim (Finney and others 2011). FSim uses an ensemble method that combines a logistic model to generate fire ignitions, a simulated stream of daily weather (wind speed and

[2] If all outcomes in Z could be expressed in commensurate units, such as dollars, then the treatment effects is the change in expected total costs for the average fire, where total costs for a given fire are: $TC = \sum_k Z_k$.

direction, relative humidity) for each simulated fire "season," an algorithm that grows the fire from burned to unburned nodes (the Minimum Travel Time fire spread algorithm, see Finney 2002), and a containment algorithm (see Finney and others 2009). Fire occurrence and the growth and containment of each fire ignition are simulated over thousands of simulated fire seasons for a given landscape. The individual fire outcomes are summarized across all simulated seasons to characterize a landscape's fire regime.

Inputs for FSim include information that describes the spatial fuels and terrain on the landscape (elevation, slope, aspect, surface fuel model, canopy cover, canopy height, canopy base height, and canopy bulk density), and data on historical weather drawn from a representative Remote Automated Weather Station (RAWS). Fuels and terrain data are static on the landscape in the sense that FSim does not alter these variables from one simulated day to the next, or from season to season). FSim generates simulated weather streams for every day in each simulated fire season based on statistical analysis of historical fire weather data.

FSim produces raster-format calculations of burn probability and fireline intensity at a 30-meter pixel resolution, and vector-format layers of each simulated wildfire perimeter. Burn probability is quantified as the number of times a given pixel burns (either from random ignition within the pixel or fire spread from an adjacent pixel) divided by the number of simulated fire seasons. Typically exposure analysis explores expected area burned and intensity using burn probabilities aggregating exposure from multiple fires (Scott and others 2012a). Use of the individual perimeters allow for an alternative analysis of exposure to fire on the landscape, quantifying the conditional distribution of acres burned from any single fire (Scott and others 2012b). That is, in addition to summarizing the distribution of fire sizes and burned area, the perimeters can be paired with other spatial data to characterize potential fire effects on the landscape (described below).

In our simulations we parameterized FSim to use identical ignition locations and weather conditions for the EC and PT scenarios, in order to directly attribute changes in fire outcomes to treatment effects[3]. Because the only difference between the pre- and post-treatment simulations is the surface and canopy fuel conditions across the landscape, the effect of fuel treatments is isolated from potential differences in weather, ignition frequency, and fire management policy. The simulated fires from each scenario are then used to compare pre- and post-treatment differences in fire size and intensity, estimated suppression costs, and exposure of HVRAs to fire.

Suppression Cost Modeling

[3] There can also be differences in fire size that result from spotting, which is stochastically determined in FSim, although this is assumed to account for negligible differences in fire outcomes.

Fuel treatments do not directly affect the cost of suppressing large wildland fires, but could indirectly affect costs by altering fire outcomes that are likely to change the strategies used to manage fires. Fuel treatments could lead to reductions in burn severity (Wimberly and others 2009, Martinson and Omi 2008), which may allow fires to be managed with less aggressive suppression responses and could lead to lower suppression costs. However, a less aggressive suppression response may ultimately lead to longer-duration fires and increased area burned, which could result in costs on par with or higher than more aggressive strategies (Gebert and Black 2012). Alternatively, fuel treatments could allow for more aggressive suppression responses, for instance more opportunities for direct attack because of reduced fire intensity (Hudak and others 2011). Our modeling approach does not directly account for the impacts of changed suppression tactics.

Changing fire size distributions resulting from a fuel treatment could also affect suppression costs. Fire size (i.e., burned area) is a primary factor associated with suppression costs. Fuel-treated areas may slow the spread of fires, increasing the chance that a given fire can be contained earlier and at a smaller size. In this study, the difference in burned area is the primary factor that results in suppression costs differences resulting from fuel treatments.

The effects of fuel treatments on suppression costs are estimated using a regression cost model developed by the U.S. Forest Service. The large fire cost model (Gebert and others 2007) is a regression model built from historical fire cost data that estimates per acre and final fire costs as a function of total fire size, fire environment variables (e.g., slope, aspect, fire weather), and values at risk (e.g., distance to town, total housing value within 20 miles). For the purposes of the fire cost model, large fires are defined as fires at least 300 acres in size. The cost model is embedded within the Wildland Fire Decision Support System for cost containment guidance and is used as a performance measure to identify extreme high cost fires (Calkin and others 2011, Noonan-Wright and others 2011). The cost model was used in this analysis to estimate suppression costs for all simulated large fires that grew to at least 300 acres (~121 hectares).

Table 1 lists the variables and regression coefficients used to calculate costs for each simulated fire[4]. The model predicts suppression costs per acre for each fire, which is then multiplied by acres burned to get total costs for each fire. Because fires are simulated using the same ignition points and weather information, the only factors that can change a fire's post-treatment predicted cost are burned area and fuels at ignition. Note that some fires that ignite where fuels are unchanged may still have a different burned area post treatment if they burn into a fuel-treated parcel.

[4] We present and describe the model in its native format, using the English System. We later present results using metric units however.

Table 1— *Variables and regression coefficients for predicting per-fire suppression costs. The model we present is a modified version of the original cost model presented in Gebert and others (2007), updated with additional years of data and adjusted to return only USFS suppression expenditures.*

Variable	Regression format	Coefficient
Burned area	Natural log of acres burned	-0.3207
Aspect (radians)	Cosine of aspect	-0.1431
	Sine of aspect	-0.0509
Elevation (feet above sea level)	Natural log of elevation	0.3603
Distance to nearest town (miles)	Natural log of distance	-0.2623
Energy release component, cumulative frequency	Percentile (1 – 100)	0.0195
Total housing value within 20 miles of ignition ($)	Natural log of Value / 100,000	0.1422
Ignition within a Wilderness Area	Binary, =1 if ignited within Wilderness	0.3922
If ignition within Wilderness, distance from ignition point to nearest Wilderness Area boundary	Natural log of distance to boundary	-0.5856
Slope	Natural log of slope	0.1134
Fuel model at ignition:	Binary categorical variables	
Grass		(reference category)
Brush		-0.0023
Brush 4		0.5128
Timber		0.8553
Slash		0.5673
Region identifier – USFS region 6	=1 for all fires in case study	1.2028
Regression constant		1.9823
Smearing factor[1]		2.0200

[1]The smearing factor (SF) corrects for retransformation bias when converting the natural log of cost per acre (the regression dependent variable) to cost per acre in dollars (see Duan 1983).

Analysis of HVRA Exposure to Wildland Fire

We present two complementary methods to quantify HVRA exposure to wildland fire, which differ in their use of fire simulation outputs. The fundamental premise of both approaches is the coupling of spatially resolved fire characteristics with maps of HVRAs. For illustrative purposes we drew spatial data for three socioeconomic and ecological HVRAs from a broader set of HVRAs identified collaboratively by Deschutes staff and stakeholder groups (Northwest Fire Learning Network 2012): the wildland-urban interface (WUI), stream reaches and key watersheds identified as habitat for Threatened and Endangered aquatic species (TE), and old-growth ponderosa pine (*Pinus ponderosa*) and dry mixed conifer trees (OG). Comparative exposure analysis illustrates effects of treatment by comparing results for the existing conditions and post-treatment modeling scenarios.

In the first exposure analysis method, we adopt a novel approach that overlays fire perimeters with HVRA maps. Unlike the use of aggregated pixel-based burn probabilities, this approach enables the quantification of the potential impacts on a per-fire basis. In turn this allows for quantifying the distribution of conditional HVRA area burned. In cases where fuel treatments reduce fire spread potential, we anticipate that HVRA area burned will decrease under the post-treatment modeling scenario. This information can be especially useful where the spatial extent of burning can influence HVRA response to fire. This approach is limited, however, in that simulation results do not output fire intensities (flame lengths) on a per fire basis.

As a complementary method, therefore, we also quantify differences in HVRA exposure by comparing expected area burned by flame length category. Conditional burn probabilities output by FSim quantify the likelihood of fire at a given flame length, conditioned on the pixel burning. Using these outputs, expected area burned is calculated as the sum of the area for a given HVRA expected to burn under each of the six flame length categories[5] and is calculated as:

$$Expected\ Area = \sum_{\mathrm{i}=1}^{6} BP_{fl_i} \times A \qquad (5)$$

where $BP\ fl_i$ is the burn probability at the i^{th} flame length category and A is the area for each 30 x 30- m pixel (i.e. 0.09 hectares). Fire intensity is an important fire outcome because even if an area of HVRA burns, a low-intensity fire may cause relatively little damage as compared with a high intensity fire. Assessing only the area burned may understate potential impacts of a fuel treatment if the distribution of fire intensity shifts due to treatment. In cases where fuel treatments reduce fire likelihood and/or intensity, we expect the distribution of expected area burned to shift towards lower intensities under the post-treatment modeling scenario.

Case Study: Deschutes National Forest, Oregon, U.S.

Figure 1 provides a map of the analysis landscape (209,207 hectares) and the project area, most of which is located within the Deschutes National Forest (DNF) (58,680 hectares total; 45,320 hectares Forest Service) in west-central Oregon. The analysis landscape extends beyond project boundaries to account for fire spread from remote ignitions onto the project area, and vice versa. Most of the landscape is comprised of ponderosa pine (*Pinus ponderosa*) and dry mixed conifer forest types, characterized

[5] FSim generates conditional burn probabilities for six flame length categories: < 2 ft (0.6 m), 2–4 ft (0.6–1.2 m), 4–6 ft (1.2–1.8 m), 6–8 ft (1.8–2.4 m), 8–12 ft (2.4–3.7 m), > 12 ft (3.7 m)

by frequent, low-severity fire. The western portions of the landscape, however, include wet mixed conifer forest types, with mixed fire severity and return intervals between 35 and 150 years. The broad treatment goals are restoring forest ecosystems, promoting resiliency, and protecting HVRAs.

DNF staff provided data on vegetation and fuel layers reflecting existing conditions (pre-treatment) as well as treatment polygons and post-treatment fuel conditions. In total 27,036 hectares (about 46% of the project area) are projected to receive treatment during the planning period from 2010 - 2019[6].

[6] Details on the how fuel treatments were modeled, including changes to surface and canopy fuels and assumed treatment longevity, are presented in Thompson and others [in review] and can be made available from the authors.

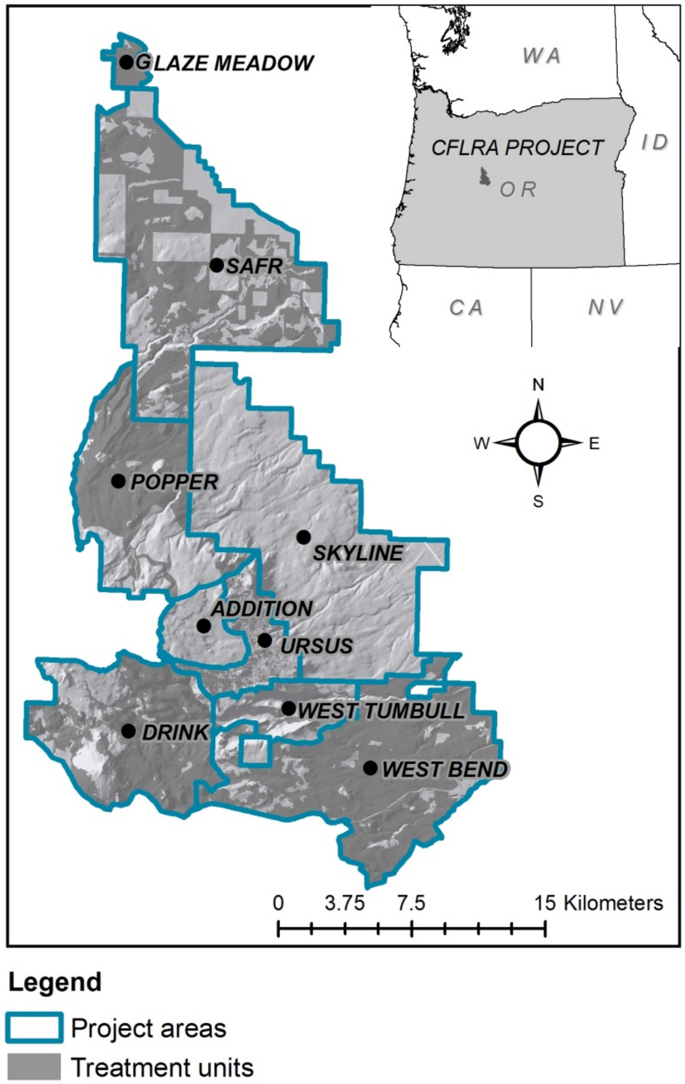

Figure 1— Map of case study landscape, with project areas and treatment units highlighted. The project areas (excluding Skyline) are located within the Deschutes National Forest, in west-central Oregon.

Results

Table 2 presents estimates of the expected outcomes for total area burned, area burned in the wildland-urban interface (WUI), threatened and endangered aquatic species habitat (TE), and old-growth forest stands (OG). Treatment effects (the difference between existing conditions and post-treatment outcomes) are also presented. Results suggest that fuel treatments are effective at reducing the expected final size of fires, which then reduces expected suppression costs and expected HVRA area burned. Suppression costs for the average fire are reduced by nearly $600,000 after treatment (about 6%). Exposure to potential damage from fire is also lower, with HVRA area burned reduced by between 10 and 16% post treatment.

Table 2—*Mean simulated fire outcomes under existing and post-treatment fuel conditions, with bootstrapped errors presented in parentheses. The regression model used to estimate per-fire suppression costs is not valid for fires smaller than about 121 hectares (see Gebert and others 2007). Some ignitions in the simulated dataset that were greater than 300 acres under existing conditions were less than 300 acres in size post treatment; these observations are excluded from the PT suppression cost estimates.*

			Highly Valued Resource and Asset (HVRA) Area Burned		
	Fire size, ha	**Suppression cost, 2010 $**	**Wildland-urban Interface, ha**	**Threated and Endangered aquatic species habitat, ha**	**Old growth stands, ha**
Existing Conditions (EC)	3,855 (77.13)	8,990,166 (130,967)	3,368 (75.78)	844.0 (22.53)	1,206 (25.45)
Post-Treatment (PT)	3,431 (73.49)	8,407,933 (135,815)	2,996 (72.06)	701.4 (20.61)	1,077 (24.47)
Difference (PT – EC)	-423.9 (18.13)	-582,233 (185,860)	-372.2 (17.04)	-142.6 (6.425)	-129.0 (5.474)

Bootstrapped standard errors estimated using 1,000 replicate samples, where the size of each sample is equal to the total number of fires in the simulated distribution, or 5,667. Sampling for each replicate occurs with replacement.

The effects of fuel treatments can be further clarified by examining the intensity at which fires burn pre- and post-treatment in areas with HVRAs. Figure 2 summarizes the distribution of area burned for each HVRA by flame length category. Shorter flame lengths (category one) indicate a low-intensity fire, while longer flame lengths (up to category six) indicate high-intensity fire.

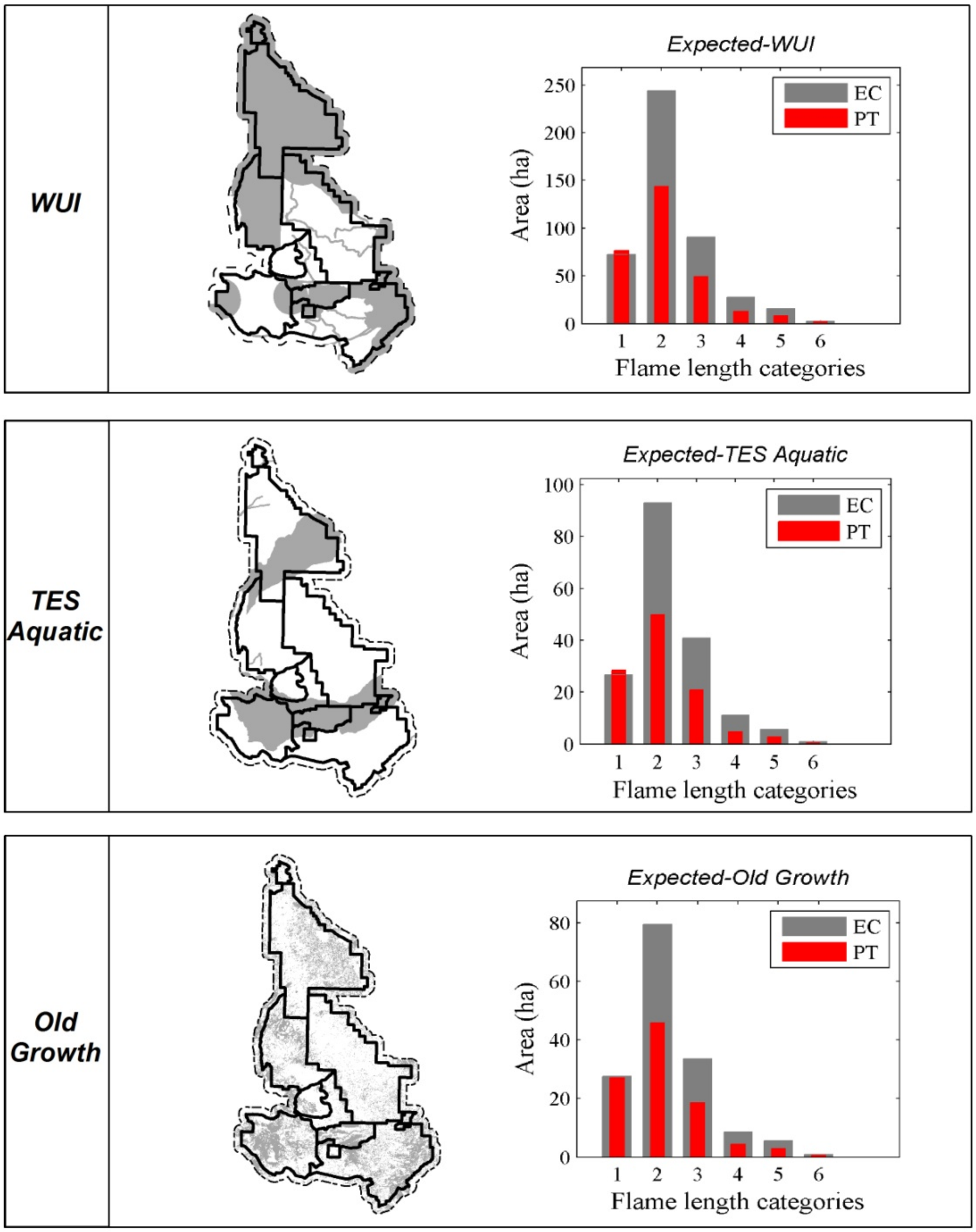

Figure 2— Distribution of expected HVRA area burned by flame length categories on existing conditions (EC) and post-treatment (PT) landscapes. Panels on the left indicate the current geographic distribution of each mapped HVRA, which influences the degree of likely exposure to wildland fire.

Unlike results from Table 2, which include all simulated fires within the analysis area, results in Figure 2 are clipped to a 1-km buffer around project areas. The expectation is a stronger signal of treatment effect, due to capturing a relatively higher proportion of fires that do intersect with treated areas. Consistent with the results of Table 2, Figure 2 shows that less area of each HVRA is burned after treatment (i.e., the bars are lower on average). But there is also evidence that the relative distribution of shifts towards lower fire intensities after treatment. For example, area burned at the shortest flame length increases after treatment in the WUI and in threatened and endangered species habitat, but area burned at longer flame lengths decreases. Similarly, area burned in old-growth forest stands decreases at the highest intensities, but stays about the same at the lowest intensities.

Discussion

The primary benefit of this case-study analysis is that it gives managers and planners a common language and set of metrics to make decisions over potential fuel treatments. We do not, in this exercise, make a conclusion about whether the proposed treatment on the Deschutes National Forest should proceed. However, managers could compare treatment effects across multiple landscapes when deciding how to allocate limited fuel treatment budgets to achieve the greatest beneficial impact. How managers might weigh changes in risk to the different HVRAs is not known, but the simulation results provide enough information to facilitate tradeoffs in decision making.

There are several limitations and conditioning factors to the existing study. First, results are contingent on the respective accuracies of input landscape and fuels data, of assumed changes to fuel conditions after treatment, and of wildfire simulation and suppression cost models. Second, the suite of prospective landscape treatments we modeled could change due to the realities of budgets and project planning, and in fact there have already been changes made to plans for treatment implementation. Third, presentation of only average results could mask important variability in the distribution of possible fire outcomes. Fourth, conclusions from the results are limited to assessments of exposure to risk, rather than predictions of effects on HVRAs. The fire simulations allow us to examine the likelihood that a particular parcel is burned pre- and post-treatment, but we do not make any predictions of the magnitude of potential impact on HVRAs due to fire. Fifth, we do not model any activities related to the initial attack suppression efforts. Changes in fuels may create more favorable conditions for containing a fire early; we assume that all ignitions that “escaped” prior to fuel treatments would have also escaped after treatment. Modeling initial attack efforts would enable exploration of tradeoffs across management investments in preparedness, fuels, and suppression response. This is left as an area of future research.

Another logical research extension would be to compare, both within and between landscapes, the relative effects of varying treatment sizes and spatial patterns, rather than the single proposed treatment analyzed here. It may be that spatially targeted treatments, even at a smaller scale, can provide the greatest return on investment for a fuel treatment program. Finally, decision support for fuel treatments cannot be complete without comparing the potential effects of the treatment to the costs of treating the landscape. These costs are not explicitly considered here, but would be useful for comparing a menu of potential treatment options.

Yet another potential avenue of research is determining the appropriate spatial scale at which to assess the effectiveness of treatments. Only considering simulated fires that intersected treated areas would over-predict treatment effectiveness, due to the fact that in any given area, there is a very low probability a treatment will actually experience fire over the course of a fire season (Campbell and others 2012). This is a critical rationale for the use of burn probability modeling to analyze effectiveness (Ager and others 2010). By contrast, considering a very large study area would tend to dampen treatment effectiveness by including a large set of fires that never interact with treated areas. For instance, suppression cost reductions for fires igniting within treated areas averaged 35% (Thompson and others 2013b), whereas across the entire analysis area, suppression cost reductions averaged 6% (Table 2). We might expect similar variation in estimates of treatment effect were the results from Figure 2 to include a different buffer width. Future work could explore how estimates of treatment effectiveness are sensitive to spatial scale, and with geospatial techniques, could possibly seek to generate smoothed treatment response surfaces.

Summary

This paper examines the question of whether landscape-scale fuel treatments can reduce risks and costs associated with large wildland fires. A simulation-based assessment of fire outcomes before and after a proposed treatment in a case-study landscape (the Deschutes National Forest) suggests that treatment can reduce area burned of highly valued resources and assets, and reduce direct costs of managing large wildfires. Fires that burn the treated landscape also tend to be less intense, leading to a reduction in the area of highly valued resources and assets that burn at the highest and most damaging intensities. These treatment effects can be interpreted as the effect of fuel treatments on the exposure to risk from wildland fire.

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