

FINAL REPORT

Evaluating spatiotemporal tradeoffs under
alternative fuel management and suppression
policies: measuring returns on investment

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List of Abbreviations and Acronyms

- **EC:** existing condition
- **eNVC:** expected net value change
- **FSim:** the Large Fire Simulator, a stochastic fire simulation model.
- **FRCS:** Fuel Reduction Cost Simulator
- **FVS:** Forest Vegetation Simulator
- **L(AB):** leverage as a function of area burned
- **L(\$):** leverage as a function of costs (U.S. dollars)
- **L(NVC):** leverage as a function of expected net value change.
- **PODs:** potential wildland fire operations delineations
- **PT:** post-treatment;
- **Spatial SCI:** Spatial Stratified Cost Index

Keywords

Risk; uncertainty; burn probability; leverage; cost effectiveness; modeling; encounter rates; highly valued resources; fuel treatments; fire suppression

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Abstract

The primary theme of our study is the cost-effectiveness of fuel treatment at multiple scales, addressing the question of whether fuel treatments can be justified on the basis of saved suppression costs. Our study was designed to track the influence of a dollar invested in fuel treatments on final fire outcomes, and to quantify this influence in terms of both financial and risk-based metrics. We focused on the nexus of fuels management and suppression response planning, designing spatial fuel treatment strategies to incorporate landscape features that provide control opportunities that are relevant to fire operations. We also aimed to demonstrate a proof-of-concept modeling approach for approximating alternative fire suppression strategies. We used the concept of leverage, quantified frequency-magnitude distributions for fire-treatment and fire-fire encounters, and demonstrated how they vary with alternative fuels management and suppression response policies.

As a first step, we performed a synthesis of the relevant literature on fuel treatments impacts on suppression costs, and aimed to include these insights into our model framework development. Two key conclusions were: 1) to account for the inherent uncertainty of when and where wildfires will occur, evaluations of return on fuel treatment investments must use a spatial, risk-based framework; and 2) the relative rarity of large wildfire on any given point on the landscape and the commensurate low likelihood of any given area burning in any given year suggest a need for large-scale fuel treatments if they are to have an impact on risk. We chose the Sierra National Forest as our study site, due to previous work providing relevant data and analytical products, and because it reflects a microcosm of many of the challenges surrounding contemporary fire and fuels management in the western U.S., including potential for large, long-duration fires and corresponding potential for high suppression expenditures. We designed two separate modeling frameworks, one to address alternative fire suppression responses and the other to optimize fuel treatments. Both made use of the Large Fire Simulator (FSim), a stochastic fire simulation program that generates maps of annual burn probability and conditional flame length probability, a list of fires with their corresponding sizes, dates, locations, and durations, and a set of fire perimeters. These outputs were utilized to ascertain the impact of alternative fire suppression response and fuel treatments on fire size and burn probability.

Modeling results generally confirmed that fire-treatment encounters are rare (such that median suppression cost savings are zero), that treatment effects are most pronounced within their boundaries and decay rapidly with distance, that treatment strategies can reduce risk and possibly expand opportunities for moderated suppression response, and that such changes in suppression response lead to feedbacks that limit burned area over time. Here we found that under most years the benefits of a fuel treatment investment may be negligible (from the perspective of changing fire outcomes), although under extreme (1/10,000) years the investment could yield a large return in avoided costs and damages. Over time, mean annual savings can accumulate such that return on investment approaches breakeven in terms of financial metrics alone. On top of this, high leverage rates for risk reduction suggest the possibility for positive return, but with the caveat that treatment benefits are highly uncertain and dependent on the vagaries of fire-treatment encounters. There exists ample opportunities to improve the integration of fuels management and suppression response planning.

Objectives

This project proposal was submitted under the *Fuels treatment effectiveness: Economics* task statement, Project Announcement No. FA-FON0013-0001. JFSP sought proposals that addressed the *cost effectiveness of fuel treatments at multiple scales*, and that focused on quantifying *economic trade-offs related to fuels treatment effectiveness*. JFSP envisioned that results would help managers *prioritize and evaluate the investment value of fuels treatments* in order to inform decisions regarding future budget allocations.

The primary theme of our study is the *cost-effectiveness of fuel treatment at multiple scales*, and our study plan was designed to address the JFSP task statement question of *whether fuel treatments can be justified on the basis of saved suppression costs*. Our stated primary objective was to comprehensively analyze *spatiotemporal economic tradeoffs under alternative fuel management and suppression policies*. Our process-based objectives largely related to designing analytical procedures that could answer salient questions regarding how the *spatial scales and locations of fuel treatments* influence treatment costs and subsequent cost effectiveness. Specifically, we wanted to develop the ability to track the influence of a dollar invested in fuel treatments on final fire outcomes, and to quantify this influence in terms of both financial and risk-based metrics. That is, the scope of analysis extended to include *reduced wildfire risk* to highly valued resources and assets in addition to *avoided suppression costs*. Project objectives also related to effective science delivery, primarily through presentations and peer-reviewed manuscripts, with the aim of providing insight into future fuel and fire management planning efforts.

Over time the objectives and scope of the project evolved as conditions warranted, although the nucleus of focusing on avoided suppression costs remained. The principal change was scaling back the temporal horizon of the analysis, which had initially been proposed as a century. There were two main reasons for this change. First, upon reflection, we did not feel we could credibly project long-term economic returns given uncertainty surrounding climate change, expansion of the wildland-urban interface, technological advances in harvesting techniques and wood utilization, technological advances in suppression strategies and tactics, and future forest product market conditions. Consider, for example, prospects for the emergence of ground-based harvesting equipment used on steep slopes, of unmanned aerial vehicles used for suppression activities, and of increased market competitiveness of low-carbon, distributed-scale systems for heat, power, fuel, and bio-products.

Second, and more importantly, this change allowed us to devote significantly more energy and resources to focus on the nexus of fuels management and suppression response planning. In light of this redirection, we updated our workflow objectives to include the following:

- Perform a comparative analysis of existing literature on approaches to estimating the influence of fuel treatments on suppression costs
- Design spatial fuel treatment strategies to incorporate landscape features that provide control opportunities that are relevant to fire operations
- Demonstrate a proof-of-concept modeling approach for approximating alternative fire suppression strategies
- Quantify the frequency and magnitude of fire-treatment and fire-fire encounters, and how they vary with alternative fuels management and suppression strategies, respectively
- Explore the extent to which near-term feedbacks from fire-fire encounters might

produce self-limitation in burned area under different suppression strategies
We developed the following hypotheses in relation to expected model findings:

- Due to the relative rarity of fire and corresponding rarity of fire-treatment interactions, median annual savings in avoided suppression costs will be zero
- Similarly, although in extreme years cost savings may be substantial, mean annual suppression cost savings will not offset upfront fuel treatment costs
- Avoided area burned, avoided suppression costs, and level of risk reduction will all increase with area treated, but with diminishing returns
- Treatment strategies designed to reduce risk could expand areas where moderated suppression response would be appropriate, and these areas can be mapped in relation to fire control opportunities
- Treatment effects will decline with distance from treatment
- Adopting alternative fire response policies under which suppression response is moderated will increase burn probabilities, fire sizes, and number of large fires in the short term, but feedbacks will limit burned area over time as the burned areas act as a form of fuel treatment.

Background

Wildland fires, an integral component of many ecosystems, can also pose grave safety concerns, result in significant socioeconomic damages, and negatively affect provision of ecosystem services. Grappling with tradeoffs around protection and restoration objectives while balancing fire responder and public safety concerns has become a major challenge for the U.S. Forest Service and other federal land management agencies. Additionally, financial risks for the Forest Service are increasing as the proportion of the agency's budget devoted to fire grows, thereby eroding available funds for other mission-critical programs and potentially compromising the agency's ability to sustain forest and grassland health (USFS 2015, Thompson et al. 2016a). Given a likely future of increasing costs and losses, the need to develop more cost-effective and sustainable approaches to managing wildland fire is apparent. So too is the need to develop improved abilities to evaluate economic tradeoffs in investments across the wildfire management spectrum.

Among others, two of the perceived benefits of fuels and forest restoration treatments are increasing suppression efficiency and reducing suppression costs (Snider et al. 2006; Moghaddas and Craggs 2008). The Collaborative Forest Landscape Restoration Program has as an explicit objective the reduction of wildfire management costs, which spurred development of techniques to estimate possible suppression cost savings (Thompson et al. 2013). In practice these techniques have been applied to evaluate avoided suppression costs associated with planned treatment strategies on National Forest landscapes, but not to evaluate possible alternative strategies (i.e., the model techniques were not used to inform optimal treatment design). Expanding use of these techniques across strategies could generate richer information on economic tradeoffs and facilitate selection of more cost-effective options. Further, improved econometric models of suppression costs that incorporate spatial information associated with a fire perimeter rather than just its ignition point (Hand et al. 2016), along with advances in GIS analysis using simulated fire perimeters (e.g., Barnett et al. 2016a; Scott et al. 2017; Thompson et al. 2016b), provide an opportunity to enhance modeling rigor and yield new insights.

Critically, these economic analyses need to accurately capture the complex spatial and stochastic aspects of wildfire (Thompson and Calkin 2011; Warziniack and Thompson 2013).

The low likelihood of experiencing wildfire in a given location in a given time window means that analyses premised on a fire-treatment encounter during the treatment's effective lifespan can grossly overstate potential treatment benefits. It is important therefore to recognize the role of burn probability as a determinant of fire-treatment encounters, which are a prerequisite for treatments to change fire outcomes. All else being equal, treatments have a higher likelihood of being encountered if placed in areas of higher burn probability, and the likelihood of fire-treatment encounters increases with area treated. Information generated from spatial burn probability modeling is necessary to assess the likelihood of a given treatment ever encountering a fire, or in turn how such an interaction may alter off-site burn probabilities due to changes in on-site fire behavior. Although seemingly simple in concept, recent analyses of historical fire-treatment encounters suggest that treatments were located in areas of low burn probability – perhaps even experiencing encounters at a rate lower than what would be expected if treatments were randomly located (Vaillant and Reinhardt 2017; Barnett et al. 2016b; Campbell et al. 2012; Rhodes and Baker 2008).

Expanding the footprint of treated areas and being more strategic in the choice of where to implement treatments are two key recommendations for improving treatment efficacy (Collins et al. 2010; Finney et al. 2008; Loudermilk et al. 2014). A variety of tools and approaches have been developed to optimally locate treatments across landscapes, and provide a promising avenue for design of more cost effective strategies (e.g., Kim et al. 2009; Ager et al. 2013). However, opportunities to expand the spatial scope of treatments are constrained by practical factors including access in many areas (North et al. 2015b), and current rates of treatment are but a fraction of the scale of area burned by wildfires (North et al. 2012b; Barnett et al. 2016b). Therefore, an increasing role exists for using unplanned ignitions to manage fuels in selected areas and under selected conditions (North et al. 2012; North et al. 2015a).

Despite growing recognition of the need for more fire, little work is being completed on evaluating, modeling, and analyzing how, where, and under what conditions the footprint of fire could be expanded on the landscape, and with what consequences. That is to say, although the need for expanding the use of beneficial fire is well recognized, how to do so is not well understood in terms of a pathway forward. While, in certain areas, experience with fire use is strong, gaps remain in current approaches to modeling fire suppression. A clear need exists for model-based evaluation of alternative response strategies in order to anticipate costs and consequences of leveraging unplanned ignitions, as well as improving understanding of unknowns and uncertainties (Riley and Thompson 2017). When coupled with recent advances in spatial fire planning that pre-identify potential fire control locations (O'Connor et al. 2017; Thompson et al. 2016c), fire managers could be presented with a far richer informational basis to facilitate safe and effective changes in suppression response.

In this study we attempt to weave these themes – suppression costs, burn probability, fire-treatment encounters, spatial treatment optimization, and alternative response strategies – into an overarching analysis framework that can begin to address questions of fire economics and risk.

Materials and Methods

Foundations, Study Area, and Study Design

Following our workflow objectives, we began by performing a comparative analysis of the existing literature on fuel treatment effects on suppression costs. We created a conceptual economic model of fuel fire-treatment encounters (Figure 1) to orient our analysis, and discussed

factors that influence fuel treatment costs and suppression costs. For the literature review of relevant studies, we limited our focus to the financial considerations facing land management agencies that invest in and implement fuel treatments, and that incur wildfire suppression expenditures (highlighted in the grey box in Figure 1). We compared three studies that varied by geographic region, spatiotemporal scope, and assumptions about factors driving changes in suppression costs (Fitch et al. 2013; Taylor et al. 2013; Thompson et al. 2013).

Key findings from this synthesis served as a starting point for development of our modeling framework. Two themes in particular emerged, which are consistent with points made earlier in this report, but warrant repeating given their importance to our study design. First, to account for the inherent uncertainty of when and where wildfires will occur, evaluations of return on fuel treatment investments must use a spatial, risk-based framework. Second, the relative rarity of large wildfire on any given point on the landscape and the commensurate low likelihood of any given area burning in any given year suggest a need for large-scale fuel treatments, if they are to have an impact on wildfire effects. Thus, in order to save large amounts of money on fire suppression, land management agencies may need to spend large amounts of money on large-scale fuels treatments.

The review article resulting from the synthesis effort was published in *California Agriculture* (Thompson and Anderson 2015), which entailed discussing the paper's relevance to California. We highlighted the fact that suppression costs in California are among the highest in the nation, particularly for the U.S. Forest Service (Thompson et al. 2015). We also highlighted the need for similar cost effectiveness analysis tailored to the geographic and socioeconomic conditions of California, and offered that on publicly managed lands in the Sierra Nevada and Northern California, fuel treatment strategies could be designed to set the stage for increased rates of prescribed and managed wildfire (North et al. 2012).

The interest in porting avoided suppression cost methodologies to the Sierra Nevada region of California opportunistically dovetailed with contemporaneous work Co-PI Thompson was involved with on the Sierra National Forest (SNF) as part of a broader regional wildfire risk assessment. The SNF pioneered the translation of spatial risk assessment into forest plan revision, and as part of that process developed potential wildland fire operational delineations, or PODs (Thompson et al. 2016c). PODs are polygons whose boundary features are relevant to fire control operations (e.g., roads, ridgetops, and water bodies), and can provide a useful spatial construct to summarize risk and plan strategic response to unplanned ignitions accordingly.

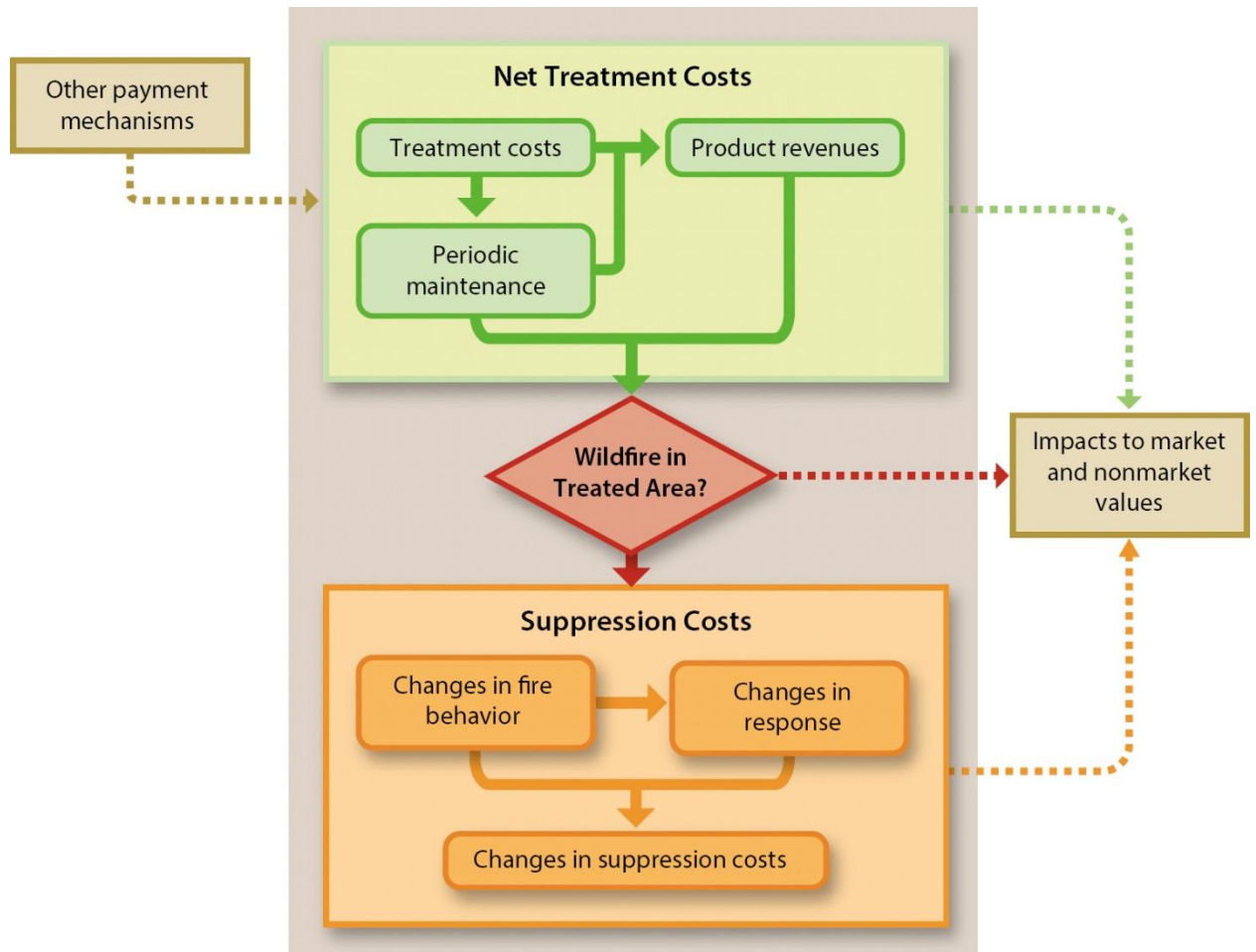


Figure 1. Model of the primary financial aspects of fuel treatment-wildfire encounters. (Thompson and Anderson 2015)

Recall our objective to strengthen the nexus between fuels management and suppression response planning, and to accomplish this in part by designing spatial fuel treatment strategies that incorporate landscape features that are relevant to fire control operations. In pursuit of this objective, we investigated the opportunity to leverage the POD network developed on the SNF, with the idea to use each POD as the spatial unit of analysis for fuel treatment prioritization. Locating and prioritizing treatments within areas delineated by fire control opportunities is inspired by the idea to use treatments to create “anchors” to facilitate fire management operations (North et al. 2015). This concept is directly related to the hypothesis that treatment strategies effective at reducing risk could expand areas where moderated suppression response would be appropriate, and these areas can be mapped in relation to fire control opportunities (i.e., PODs).

Fortunately the SNF is a well-studied location, such that many of the other building blocks for our analysis were readily available. This includes spatial risk assessment results built with local input and data (Thompson et al. 2016c), fire behavior modeling underpinning the risk assessment (Thompson et al. 2016b; Scott et al. 2017), maps of fuel treatment constraints (North et al. 2015b), and biophysically-driven fuel treatment prescriptions (Scott et al. 2016). Beyond these practical considerations, we felt the SNF made a useful case study location because it reflects a microcosm of many of the challenges surrounding contemporary fire and fuels management in the western U.S.: potential for large, long-duration fires; corresponding potential

for high suppression expenditures; proximal at-risk human communities; accumulation of hazardous fuel loads due in part to fire exclusion; and significant treatment and restoration needs. Over the course of the study we subsequently interfaced with local SNF line officers and staff to better understand local context, to ground-truth assumptions, and to shed light on strengths and limitations of our modeling framework.

Figure 2 presents a map of the SNF within the broader study area, and identifies the analysis area within which we ran the Large Fire Simulation (FSim; Finney et al. 2011). Figure 3 presents a zoomed-in map of the SNF landscape, with POD boundaries and suitable treatment locations identified. We used this SNF landscape to investigate fuels treatment strategies on the basis of POD-level metrics. To do so, we generated a range of optimal fuel treatment strategies under different budget levels, re-simulated fire on these treated landscapes, and produced vectors of outputs including fire-treatment encounter rates, along with subsequent changes in burn probability, annual area burned, risk (net value change), and suppression costs. We combined evaluation of avoided area burned, avoided suppression costs, and avoided damages under the umbrella of leverage (e.g., Boer et al. 2009; Price et al. 2015) to explore multiple dimensions with which to characterize return on investment. We further re-parameterized FSim to demonstrate proof-of-concept of modeling alternative fire suppression strategies on the same landscape (Riley et al., in review) and to examine the frequency and magnitude of feedbacks that prevent burning in the future due to alternative fire suppression strategies.

Fuel Treatment Analysis: Model Workflow and Leverage Metrics

Figure 4 presents the basic workflow for our fuels treatment modeling framework. Beginning in the upper left, the existing conditions (EC) landscape is the foundation for fire behavior modeling and treatment design, and serves as the basis for creating hypothetical post-treatment (PT) landscape conditions. The primary analytical steps highlighted in this diagram are optimization to generate efficient spatial treatment strategies, and stochastic fire simulation to evaluate these strategies. Additional modules not directly illustrated in this framework are: treatment location, prescription, and cost modeling; spatial risk assessment; and suppression cost modeling. Optimal treatment strategies are developed as a function of treatment costs, harvest volume, feasible treatment locations, and expected net value change (eNVC). All of these measures are summarized for each POD, making the choice of whether to treat all feasible locations within a given POD the primary decision variable.

Boxes highlighted in grey are used in leverage calculations, the equations for which are presented in the upper right of the figure. All leverage metrics are calculated as ratios, with the numerator expressing the net change due to the treatment strategy, in terms of annual area burned, suppression costs, and landscape expected net value change. The denominators reflect an attribute of the treatment strategy itself, in terms of area treated, treatment cost, and expected net value change within treated areas. Individual modeling components are described below. By also calculating fire-treatment encounter rates (described below), we are able to generate frequency-magnitude distributions that characterize treatment effects on avoided annual area burned and avoided suppression costs. In other words, in addition to asking how many times simulated fires interacted with treated areas, we can also ask for instance how often such interactions resulted in cost savings above a certain threshold.

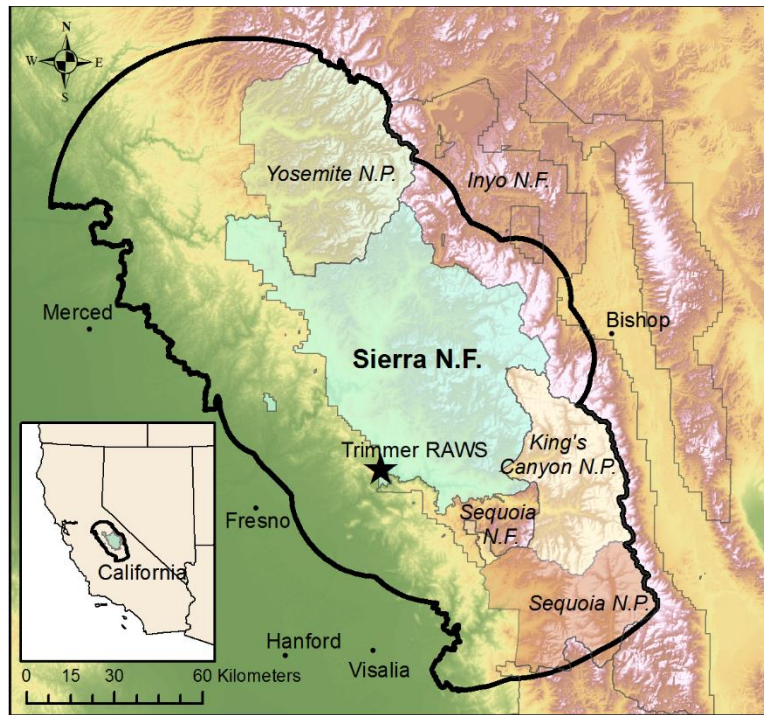


Figure 2. The study area. FSim was run with ignitions occurring inside the black polygon (the Fire Occurrence Area). The landscape file (lcp) extent is identical to the boundaries of this figure. Burn probability results were later clipped to the Sierra National Forest boundary, to confine analysis to the national forest boundaries.

Fuel Treatment Eligibility, Prescription, and Cost Modeling

We began our fuel treatment modeling by removing from consideration any locations that weren't operationally or administratively feasible for mechanical treatment. To do this we relied on previous research mapping treatment opportunities by (North et al. 2015b), specifically using their Scenario D, which offered the loosest constraints. We then used random forest regression modeling to assign each pixel on the landscape to a unique tree list corresponding to an existing Forest Inventory and Analysis (FIA) plot following the methodology of Riley et al. (2016). These tree list data formed the basis for subsequent modeling of mechanical harvesting and treatment costs, as described below.

Forest treatments simulated for the SNF are those described by Scott et al (2016), and were designed to reduce the rate of spread and intensity of surface fires as well as the probability of crown fire. The treatment logic assumes surface fuels are treated after mechanical thinning, which here we model as under burning. To simulate these forest treatments, we used the Western Sierra variant of the Forest Vegetation Simulator (FVS 2016) to trigger a thin from below cutting. We computed harvested volume for use in treatment optimization. We then estimated treatment costs for the treatments using the Fuel Reduction Cost Simulator (FRCS 2010) assuming mechanical ground-based whole-tree harvesting. To estimate costs of under burning to dispose of activity fuels generated from implementing the crown cover reduction treatment, we employed the model developed by Calkin and Gebert (2006). Details on settings for these three models are available from the authors. Cost estimates were converted to 2012 dollars using the GDP deflator (BEA 2016) in order to be consistent with modeled suppression costs.

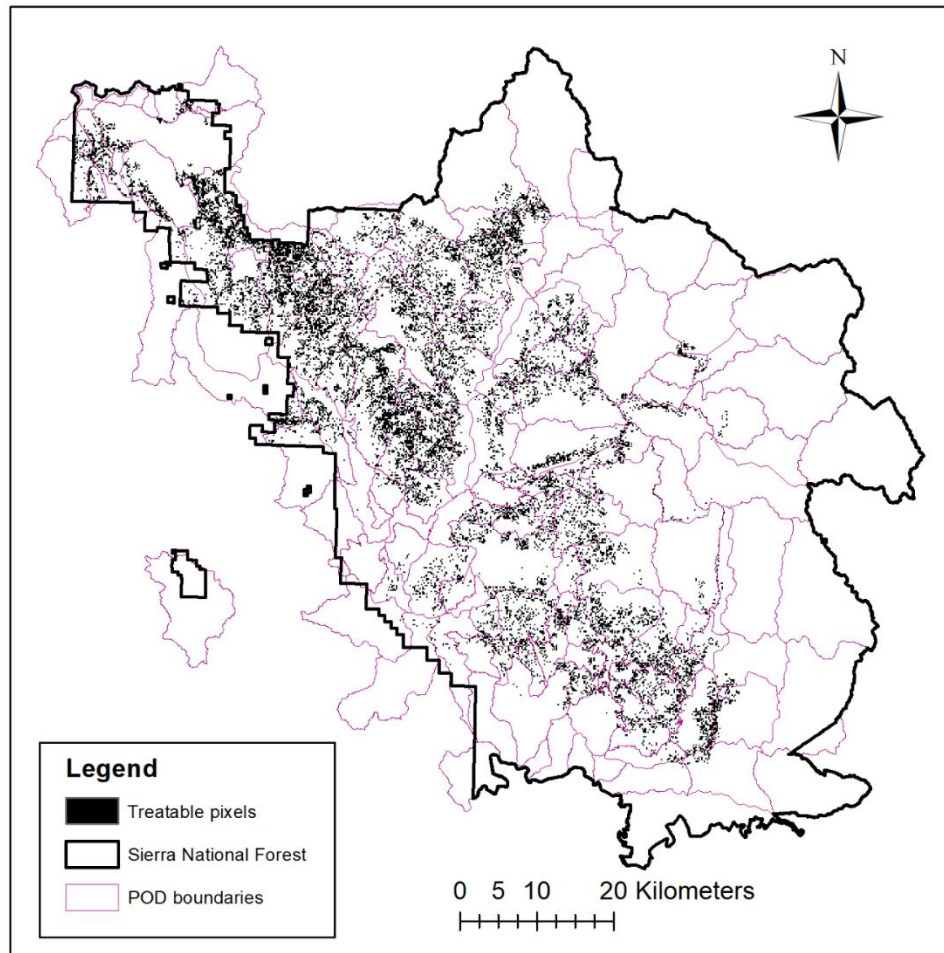


Figure 3. Sierra National Forest, POD boundaries, and feasible treatment locations. The treatment locations were determined by applying the constraint filters of North et al. (2015b) plus additional filters developed on the basis of economic viability.

The methods described above provided per-hectare treatment costs for each operationally feasible tree list present on our modeling landscape. We then further removed from consideration tree lists on the basis of low values of canopy cover reduction or trees removed per acre to avoid estimating what would likely be artificially high treatment costs due to harvest parameters outside of what would normally be implemented on the ground. This resulted in 199 unique tree lists that collectively account for 49,490 ha eligible for treatment. We summarized these results on the basis of the relative proportion of each unique tree list within each POD, resulting in a total treatment cost estimate per POD. Lastly, we applied two additional filters for treatment, requiring a minimum treatable area within a POD of 202 ha, and limiting consideration to PODs with a net negative eNVC value (meaning net loss from wildfire). Although PODs with a positive net value change (meaning net benefit) could be candidates for application of prescribed fire for resource benefit, we did not consider that option in this analysis, choosing instead to target PODs for fuel treatments where the potential to avoid loss to highly valued resources was greatest. Applying these filters resulted in 31 PODs eligible for treatment, comprising approximately 20,640 ha.

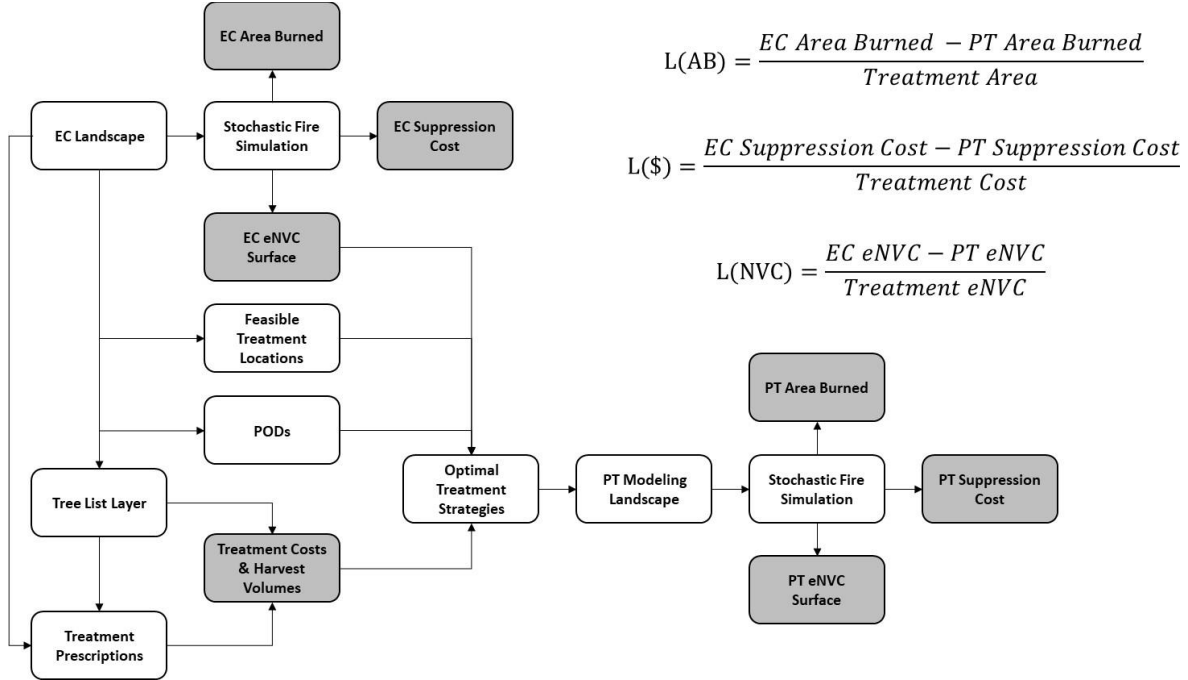


Figure 4. Optimization-simulation modeling workflow along with leverage formulas; boxes highlighted in grey form the basis for leverage calculations. EC = existing condition; PT = post-treatment; eNVC = expected net value change; PODs = potential wildland fire operations delineations; L(AB) = leverage as a function of area burned; L(\$) = leverage as a function of costs (U.S. dollars); L(NVC) = leverage as a function of expected net value change.

Treatment Strategy Optimization

We developed a single-period, bi-criteria integer programming formulation to maximize risk reduction and maximize volume harvested. The objective to maximize risk reduction uses as a proxy the total eNVC within areas feasible for treatment within each POD. The only constraint is that the total amount spent on treatment at the National Forest level must be below a defined budget level; we explored four budgetary levels: \$10.5M, \$21M, \$31.5M, and \$42M. The subsequent landscape treatment strategies we generated are comparable to existing projects funded under the Collaborative Forest Landscape Restoration Program in terms of budget levels and area treated (USFS 2017). We generated efficient frontiers comprised of twenty solutions for each budget level, and retained all optimal solutions for exploration in future research. From this set of solutions we selected six treatment strategies to feed into additional simulation analysis; one solution per budget level plus an additional two solutions at the \$21M budget.

Suppression Cost Modeling

To estimate suppression costs we leveraged a recently developed regression model of suppression costs (Hand et al. 2016). Consistent with intended use to estimate cost for nominally “large” fires, we subset the modeled fire perimeters to include only those fires that grew to be over 100 ha, and further included only fires that ignited within the SNF. Because we were estimating costs for simulated rather than observed fires, we derived fire size, maximum ERC, and ERC standard deviation (over the duration of the fire) from FSim output files. Housing value was calculated using a Python script that called the arcpy module to iteratively select for each fire all housing values inside the fire and within buffered distances of the fire and summed these

housing values. For the remainder of the predictor variables, we overlaid each fire perimeter with the predictor variable raster and found the variable of interest (mean for some variables and proportion for others) using the RMRS Raster Tool's Zonal Statistics Tool (Hogland and Anderson 2017). Lastly, we used a script written in R to estimate per-fire costs based on these predictor variables, using the coefficients presented for the ordinary least squares model presented in Table 3 in Hand et al (2016). In total costs were calculated for nearly 150,000 large fires. Only after calculating these individual fire costs could we estimate annual suppression costs, accounting for years in which no simulated fires occurred and those where several occurred. We similarly calculated distributions of annual area burned, which served as the basis for our encounter rate calculations (see below).

Fire-Treatment Encounters and Changes in Burn Probability

Similar to Barnett et al. (2016b), we defined a fire-treatment encounter as the geospatial intersection of a simulated fire perimeter with at least one treated pixel. We found the number of treated pixels burned by each fire using the RMRS Raster Tool's Zonal Statistics tool (Hogland and Anderson 2017), overlaying each perimeter with a raster of all treated pixels for each of the six treated landscapes. We converted the number of treated pixels burned into hectares, which enables calculation of total treated area burned per fire. We then annualized these results, calculating distributions of total treated area burned for each simulated fire season.

Changes in burn probability result from fire-treatment encounters that change fire sizes. To calculate changes in burn probability we subtracted the raster burn probability results of each treated FSim run from those of the calibrated run. To calculate mean reductions in burn probability at the POD level, this difference raster was summarized using the RMRS Raster Tool's Zonal Statistics tool (Hogland and Anderson 2017) in order to find the mean per POD. Mean changes in burn probability were also summarized within distance zones from treated pixels. Conditional flame length probabilities were collapsed from six into two categories (less than 4' and greater than 4') and converted into absolute probabilities via multiplying by the annual burn probability raster. The two resulting absolute flame length probability rasters were summarized to calculate mean changes in flame length probability within distance zones from treated pixels.

Fire Modeling Approach: the Large Fire Simulator (FSim)

FSim Model Framework and Model Settings

For this project, we required a simulation program that would model fire initiation and growth, landscape-level burn probability, and fire perimeters under different fire suppression and fuel treatment scenarios. We chose the Large Fire Simulator (FSim) as it has these capabilities (Finney et al 2011). Specifically, FSim contains a fire suppression module that may be activated, presenting users with the opportunity to model fires under a strategy of no suppression or suppression of various intensities (Finney et al 2009; Finney 2014). Fuel treatments can be simulated by making changes to the landscape file. Best practices for preparing input data and for calibration were followed; details are available from the authors.

Four key outputs of FSim required for this project are: 1) a raster of the annual probability of burning at all points on the landscape, 2) a list of the ignition date, location, duration, and size of each fire, 3) a raster of conditional flame length probabilities, and 4) a set of simulated fire perimeters.

Modeling Alternative Suppression Response Policies

In modeling alternative suppression response, we chose to model two scenarios from nearly opposite ends of the fire management continuum (Figure 5). Scenario 1 was calibrated to emulate annual burn probabilities and fire size distributions during the period 1992-2013, when the de facto national strategy has been full suppression on virtually all fires. Scenario 2 utilized a response policy of full suppression on all human-ignited fires and no suppression of lightning fires. This scenario consists of two separate FSim runs, of which the outputs are additive.

In order to simulate lightning-caused fires, we performed a logistic regression using the ERC on days when at least one lightning fire of any size ignited. This yielded the probability of a lightning ignition as a function of ERC. Here, we included fires of all sizes (not just large fires) since any of these fires may have the opportunity to grow large in the absence of suppression. We created an ignition density grid for lightning ignitions, which had a spatial pattern indicating ignitions increased with elevation, using kernel density of lightning ignitions within a 50-km radius. The perimeter trimming and suppression modules were turned off, so that fires were extinguished only by weather.

To simulate the other component of Scenario 2, human-caused large fires, we built the logistic regression based on the ERC on days when a human-caused fire that grew to be over 100 ha ignited. This restricted the population of fires simulated to human-caused large fires. Accordingly, we created an ignition density grid based on only human-caused large fires, which were more common near areas of population which roughly coincided with lower elevations (again, a kernel density function was performed using a 50-km radius).

When added, the burn probability grids from these two runs indicate the annual burn probability under a strategy where human-caused large fires are suppressed in a similar fashion to those in the recent historical period but lightning ignitions are not suppressed. Similarly, the two sets of fire ignitions and fire perimeters yielded by these runs were combined to form a full set of fire ignitions and perimeters under this strategy. Because the weather streams were necessarily different across the two runs, we classified the simulation years in each of the two runs into four quantiles based on total area burned, as a proxy for whether the year was an active or slow fire season. Within the quantiles, years were randomly matched (for example, simulation year 3 for the human-caused large fires was in the 4th quantile for area burned, and was randomly matched to simulation year 1005 of the lightning-caused fires, which was also in the 4th quantile for area burned).

The FSim model has a static landscape, and as such, does not limit the number of times in a year that a pixel can burn. We identified areas in which a pixel burned more than once in a model year (which would be rare if not unheard of in this ecosystem) and removed these areas during post-processing. The results presented here are based on the resulting perimeters and the burn probability raster with over-burn deleted.

We examined two types of feedbacks in area burned, which we call Type 1 and Type 2. Under Type 1 feedbacks, we counted how often a fire attempted to ignite in an area not receptive to burning due to having burned within the previous 5-10 years. Due to uncertainty in how long a recently burned area would limit fire ignition, we calculated encounter rates under two scenarios: previously burned areas limit fire ignition 1) for a period of five years, and 2) for ten years. In order to calculate the feedback rate for the five-year time period, we chose six random years of modeled fires (one of these years is considered to be the current fire year, while the other years constitute the previous five years of fires). We selected years randomly since model years are not implied to be consecutive in FSim. We completed 10,000 random draws of six years for Scenario

1, and also for Scenario 2. We overlaid the ignitions from random year 6 over the fire perimeters from years 1, 2, 3, 4, and 5. If an ignition fell inside a perimeter from the previous five years, we assumed the fire could not have ignited. If we found at least one instance where a fire would not have ignited because the ignition fell on a recently burned area, we report this case as a positive outcome under Type 1 feedbacks. In addition, we calculate the percentage of total area burned that would be avoided under the Type 1 rule. We repeated the process above for Scenario 1 and 2 with a 10-year limitation as well.

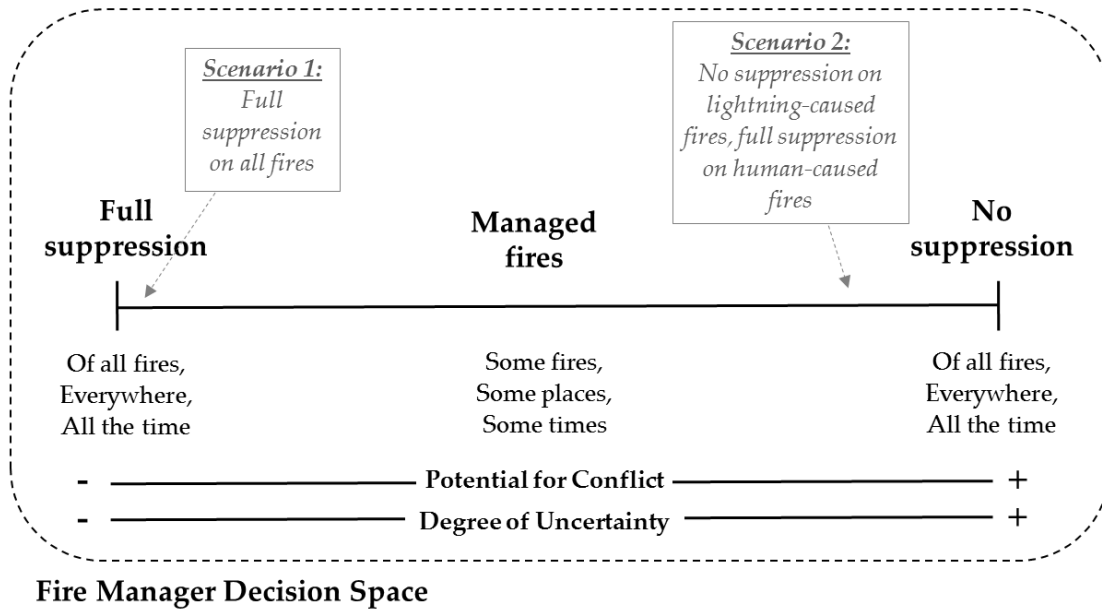


Figure 5. The fire management continuum (a simplified and stylized version of that presented in Thompson et al. (2016c)), highlighting the location of the two modeling scenarios.

Under Type 2 feedbacks, we assumed that an area would only be able to carry a spreading fire once within a five-year period. We deleted any part of a fire that overlapped with an area that burned during the previous five years. We repeated the Type 2 analysis assuming that the limitation in fire spread lasted for a ten-year period instead. The Type 2 feedback rate refers to the percent of random draws in which there was at least one instance in which a fire overlapped an area burned during the previous five or ten years. We also calculated the acreage reduction based on the deleted polygons in areas which could not re-burn under Type 2 rules.

For this feedback analysis, we considered only large fires, as FSim does not ignite fires under conditions where they are likely to remain small. The large fire perimeters were clipped to the boundary of the SNF, so all calculations of area burned and avoided area are confined to the National Forest.

Results and Discussion

Optimal Treatment Strategies and Changes in Burn Probability

Once all landscape constraints were implemented, only 8.6% of the SNF was eligible for

fuels treatment. However, this figure was several times the amount of landscape that could be treated due to budget constraints. The location of PODs selected for treatment in each budget scenario are presented in Figure 6. At higher budget levels, some of the treated PODs ended up being clustered together, especially in the northwest corner of the modeling landscape, suggesting that PODs with high risk or high volume are co-located on the landscape and preferentially selected for treatment together.

Not surprisingly, increasing the budget increased the number of PODs treated and the total treated area (Table 1). Treated area increased in a linear fashion in response to amount invested, from approximately 4,000 ha treated at \$10 million up to approximately 16,500 ha at \$40 million. Investing \$10 million in fuel treatments reduced the mean burn probability of the SNF by 3.7%. Additional investments in fuel treatments reduced burn probability in a linear fashion, by approximately 3% per \$10 million invested, with reduction in burn probability of 12% for a \$40 million investment.

Table 1. Summary of fuel treatment scenarios

Treatment Scenario	Number of PODs Treated	Area Treated (ha)	Percent of Sierra National Forest Treated	Percent Reduction in Sierra National Forest Mean Burn Probability
Budget 1	3	4,031	0.7%	3.7%
Budget 2(1) ¹	10	8,217	1.4%	6.8%
Budget 2(10)	7	7,922	1.4%	7.2%
Budget 2(20)	7	7,919	1.4%	6.7%
Budget 3	12	12,114	2.1%	9.9%
Budget 4	24	16,534	2.9%	12.0%

¹ Parenthetical number corresponds to solution number for budget level with multiple solutions selected

Figure 6 illustrates reductions in burn probability for all six treatment scenarios, in relation to PODs selected for treatment. Burn probabilities were reduced by the treatment within and adjacent to the treated area. Note that reduction in burn probability is positive (blue). Some pixels experienced a slight increase in burn probability (light brown), which is a phenomenon that has been seen in other modeling studies with FSim (Thompson et al. 2013), and is likely attributable to stochastic spotting within the model.

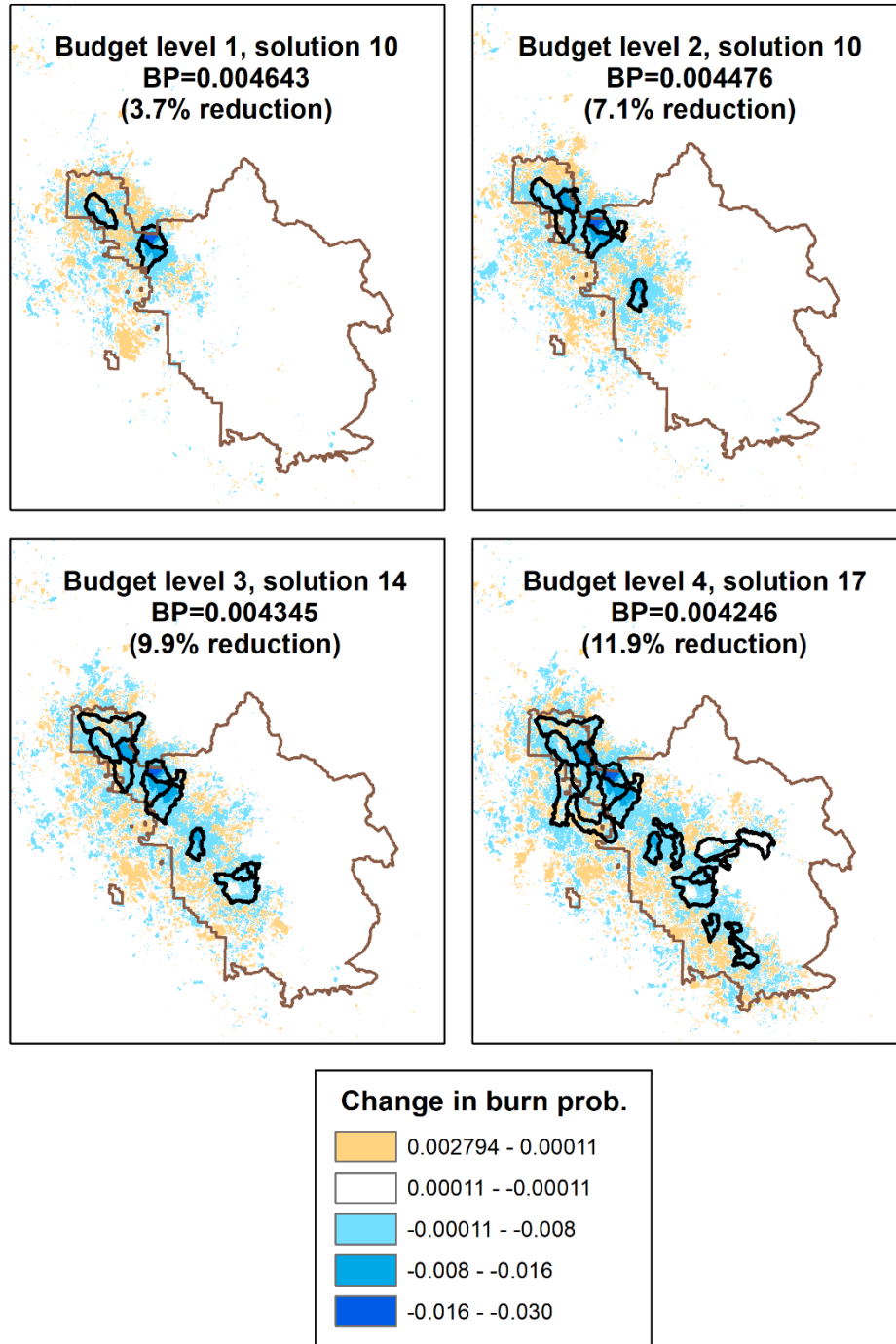


Figure 6. Modeled fuel treatment effect on burn probabilities in the Sierra National Forest. PODs selected for treatment in each of the six fuel treatment scenarios are outlined in black.

Treatment Effects as a Function of Distance to Treatment

Fuel treatments reduced burn probability within and in the immediate vicinity of treated areas (Figure 7). Within the boundaries of a treatment, burn probabilities decreased drastically

from pre-treatment conditions: 0.006-0.01 or 48-60% depending on the treatment scenario (Figure 8). Reductions in burn probability decreased sharply with distance from treatment; at a distance of 1-2 km mean reductions in probability were less than 2 in 1000, and at distances over 2 km reductions were essentially zero. The burn probabilities of some (but not most) pixels near treated areas increased slightly, likely due either to the reduced rate of spread in treated areas translating into some fires finding a new comparatively more rapid path around the treated area or to stochastic spotting in the model. Mean percent reductions in burn probability were highest for budget level 1 within the treated areas (around 60%), probably because treatments were selected for units with the greatest potential to reduce risk to highly valued resources (where risk is a product of burn probability and effect, and the treatment locations with the highest potential to reduce risk were chosen, thus it's likely they were preferentially weighted toward pixels with high burn probabilities). The next highest reductions in burn probability within treated areas were generally for budget level 2 at approximately 50-56% (although budget level 3 at approximately 52% had higher reductions than some treatment arrangements for budget level 2), followed by budget level 3 and then budget level 4 (about 48%). This may seem counterintuitive since the more money that was spent, the lower the mean percent reduction in burn probability – but this is probably a result of the pixels with the highest burn probabilities being treated first (at the lowest budget level) and as the budget expands, pixels with somewhat lower burn probabilities are treated. This pattern amongst the budget levels remained similar as distance from treatment increased, but the mean percent reduction in burn probability rapidly decreased. At a distance of 250-500 m from the treatment, reductions were about 15-22%, at 500m-1km they were about 8-13%, at 1-2km they were about 5-10%, and farther than 2 km they were negligible.

Burn probability was classified into two categories: low flame lengths were those below 4', where direct attack would likely be possible, and high flame lengths as those greater than 4'. On average, the probability of low flame lengths increased on treated pixels (Figure 9), rising by 800-1100%, while probability of high flame lengths decreased drastically on treated pixels (Figure 10), by an average of around 90%. In short, treatments reduced burn probability mainly by reducing the incidence of high intensity fire, while fires that would have burned at high intensity now burn the treated pixels at low intensity.

Similar to the pattern in burn probability as a whole, reductions in high and low flame length probability decreased with distance from the treatment (Figures 11 and 12). Budget level 1 had the highest reductions, generally followed by budget level 2, then 3, then 4.

Encounter Rates and Leverage Metrics

Table 2 summarizes fire-treatment encounters and treated area burned, on a per-fire basis as well as an annualized basis. Across all treatment scenarios the median values for treated area burned on both a per-fire and annualized basis are zero, which reflects the relatively low proportion of the landscape treated as well as the relatively low burn probabilities. Encounter rates are higher on an annualized basis, which captures the possibility of multiple fire-treatment interactions in a given fire season (the mean annual number of large fires is greater than 2 in all scenarios). At the highest budget level, 42% of the fire seasons have at least one fire-treatment encounter, but mean treated area burned is only 85.60 ha.

The magnitude of reductions in annual area burned that resulted from fire-treatment encounters were roughly an order of magnitude larger than annual treated area burned (Table 3). Although overall reductions in mean annual area burned increased with budget, the ratio of

treated area burned to reduced area burned decreased with budget. This suggests a modestly diminishing rate of return from treating more of the landscape, in terms of area burned. This result is driven in part by the objective to reduce risk, which itself is largely driven by burn probability. If leverage were determined on the basis of these fire-treatment encounters alone, the treatment strategies would come across as looking very efficient. However the treated area burned in wildfire is just a small fraction of the total area treated, and in many years no treated area is burned.

Table 4 presents mean annual suppression cost savings, with additional metrics related to savings in relation to treatment costs. Across treatment scenarios, cost savings of sufficient magnitude to offset treatment costs are in the 97th-98th percentile across all simulated fire seasons. The payback periods (ignoring the time value of money) are also presented, which range from 11 to 14 years. This length of time roughly aligns with the effective duration of fuel treatments in this location, suggesting that over time suppression cost savings could at least partially recoup initial fuel treatment investments. To account for forest products revenues, in an admittedly coarse way, the table also presents the break-even revenue amounts for each strategy, using a 10 year payback period (i.e., treatment revenue + 10 years of mean annual savings = treatment cost).

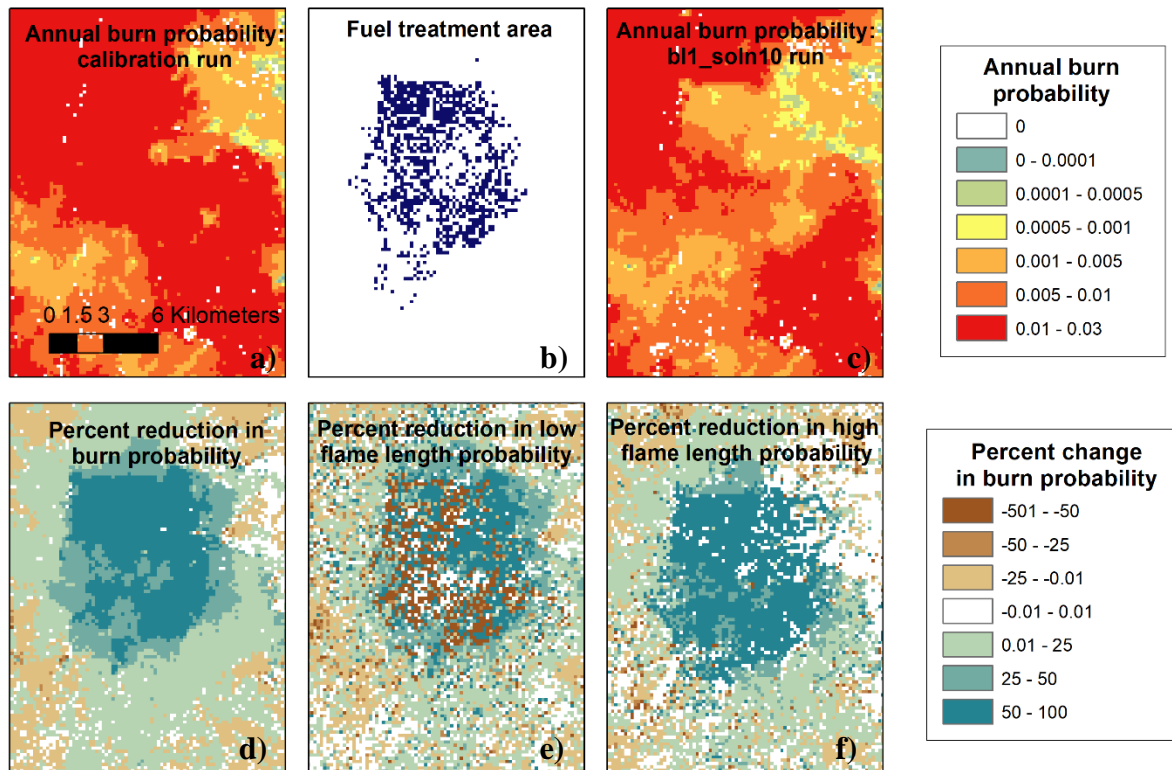


Figure 7. Reductions in burn probability are illustrated for a treated area. Each of the six windows is at the same scale and for the same extent. a) Annual burn probability for the calibrated (untreated) FSim run. b) Treated pixels. c) Burn probability for the bl1_soln10 FSim run (\$10.5 million investment in treatments). d) Burn probabilities were reduced by the treatment within and adjacent to the treated area. Note that a reduction in burn probability is positive (blue) in the lower set of illustrations. e) Low flame length probabilities generally increased within the treated area since some fires that had been high flame length were now of low flame length. f) Probability of high flame lengths decreased drastically within the treated area and adjacent to it.

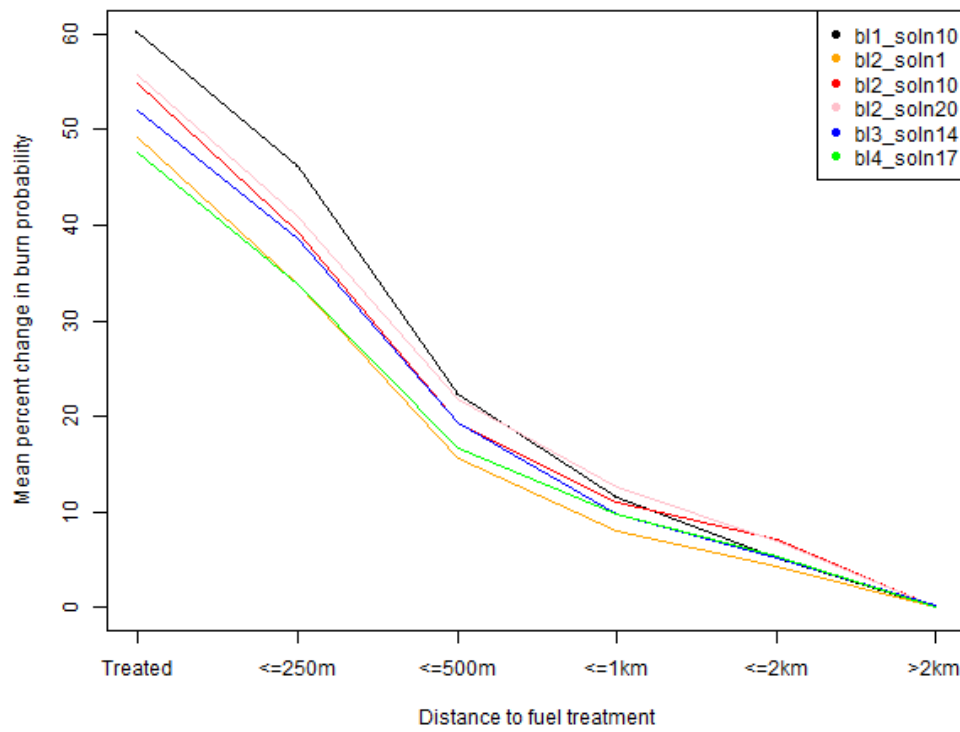


Figure 8. Percent reduction in annual burn probability due to fuel treatment for six treatment scenarios, in terms of distance from treatment.

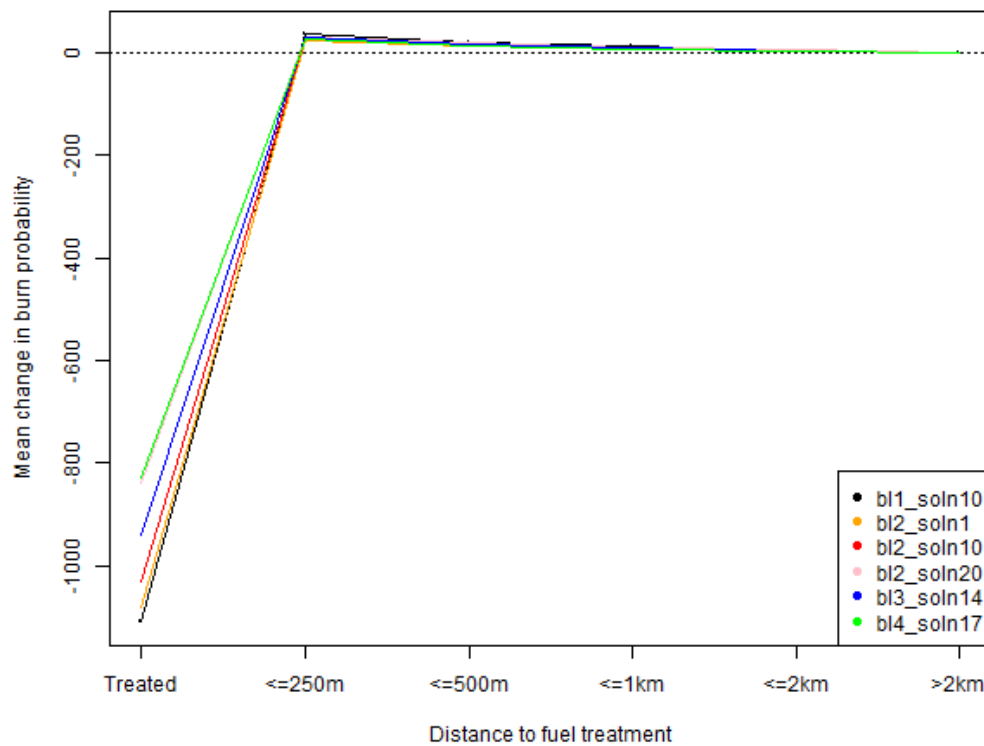


Figure 9. Percent reduction in low flame length burn probability due to fuel treatment for six treatment scenarios, in terms of distance from treatment.

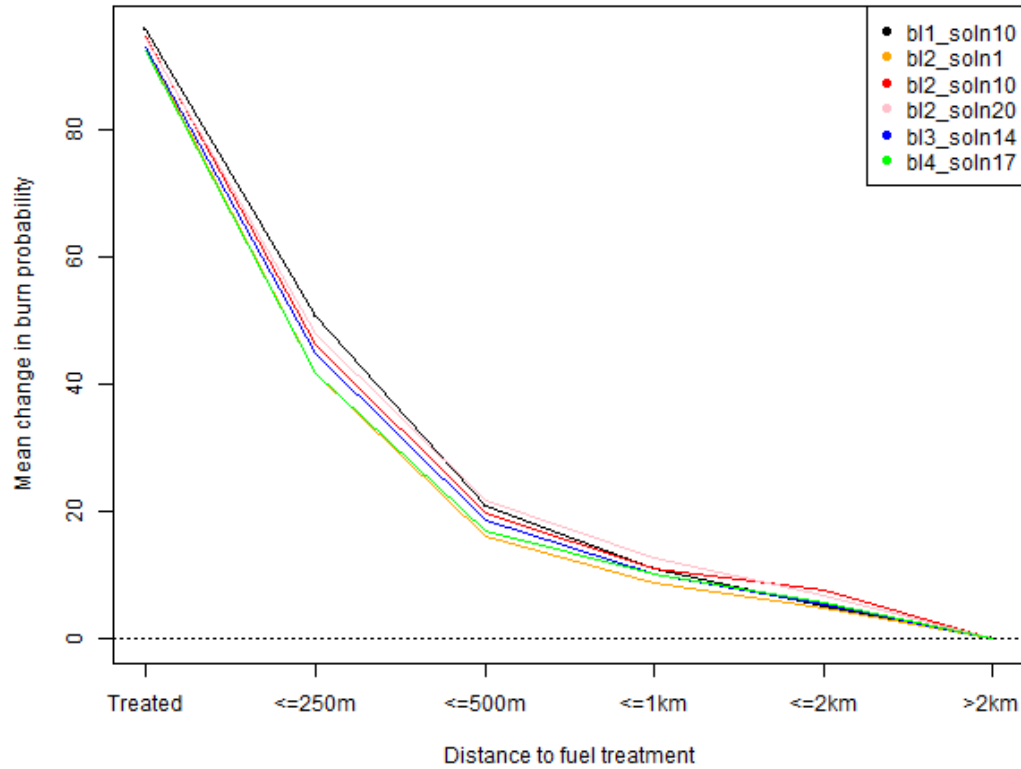


Figure 10. Percent reduction in high flame length burn probability due to fuel treatment for six treatments scenarios, in terms of distance to treatment.

Table 2. Per-fire and annualized fire-treatment encounters; summarizing treated area burned

	Budget 1	Budget 2(1)	Budget 2(10)	Budget 2(20)	Budget 3	Budget 4
Mean annual number of large fires	2.40	2.38	2.38	2.38	2.36	2.35
Proportion of fires that encountered a treatment	0.07	0.16	0.14	0.14	0.22	0.31
Mean treated area burned (ha)	9.12	20.18	19.27	18.71	28.20	36.71
Proportion of fire seasons where fires encountered a treatment	0.15	0.28	0.24	0.25	0.34	0.42
Mean annual treated area burned (ha)	21.85	47.77	45.55	44.19	66.23	85.60

Table 5 summarizes overall leverage metrics for avoided area burned, avoided suppression costs, and risk reduction (eNVC). As described above, the relative infrequency of

fire-treatment encounters coupled with the small magnitude of impact relative to the upfront investment yields low leverage rates for area burned and suppression cost. On an annual basis a hectare treated does not preclude a hectare from burning, and a dollar invested in treatment does not save a dollar in suppression costs, but as demonstrated in Table 4 the calculus looks better as the time horizon and the effective treatment duration extend.

Leverage metrics for risk reduction appear comparatively best; one unit of risk reduction within treated areas yields more than one unit of risk reduction across the landscape. This indicates that reducing burn probabilities and flame lengths both within and outside of treated areas (Figure 6), results in reduced loss or possibly benefits to highly valued resources and assets across this landscape. Figure 11 illustrates net changes in total POD-level eNVC, which confirm the finding that treatments reduce risk both within and adjacent to treated PODs. Although some PODs experience minor increases in loss (negative values), likely due to increased burn probability from stochastic spotting, the number of PODs experiencing benefits, and the magnitude of those benefits, both outweigh minor increases in loss.

Perhaps more telling are the total POD-level eNVC values after treatment (Figure 12). Not only are reductions in risk apparent in every treated POD, at each level of treatment, but several PODs transition from total net loss to total net benefit. The number of PODs with total net benefits increases with budget level. Here the connection to changes in response planning become most evident, such that within PODs with net benefits, opportunities for moderated suppression responses may increase.

Table 3. Avoided annual area burned summary

	Budget 1	Budget 2(1)	Budget 2(10)	Budget 2(20)	Budget 3	Budget 4
Mean reduction in annual area burned (ha)	99.27	193.83	201.20	195.45	280.09	343.55
Ratio of treated area burned to reduction in area burned	11.23	10.03	10.91	10.93	10.45	9.92

Alternative Fire Response Policies

We present results of two alternative fire response strategies from nearly opposite ends of the fire management continuum: Scenario 1 reflects a full suppression response on all fires, while Scenario 2 models full suppression on human ignitions and suppression only by weather on lightning ignitions. An average of 8.4 large fires per year occurred in Scenario 1, which was close to the observed number of large fires (9.1) due to calibration efforts (Table 6). In Scenario 2, lightning ignitions were more likely to grow large due to the suppression module being switched off, and average of 38.6 large fires per year occurred.

The mean annual burn probability (the average odds of a pixel burning) for the SNF was 0.0049 in the business-as-usual scenario (Scenario 1), close to the observed burn probability of 0.0053. Burn probabilities were higher along the southwest portion of the study area, and lower in the eastern portion of the study area (Figure 13a). This pattern was likely driven primarily by fuel type, with the shrub and timber-understory fuel types in the southwest portion of the study

area generally having higher rates of spread and thus contributing to more rapid fire growth than the primarily timber litter fuel types in the eastern portion of the study area (Figure 13). In the eastern part of the study area, fire spread was also checked by non-burnable areas where rocky sites occur in the Sierra Nevada Mountains.

Table 4. Avoided annual suppression cost summary

	Budget 1	Budget 2(1)	Budget 2(10)	Budget 2(20)	Budget 3	Budget 4
Mean annual avoided suppression costs (\$M)	0.72	1.67	1.79	1.60	2.50	2.99
Percentile corresponding to full offset of treatment cost	0.97	0.97	0.97	0.98	0.98	0.98
Payback period	13.82	12.01	11.16	12.50	12.01	13.36
Treatment revenue to fully offset treatment cost in 10 years (\$M)	2.76	3.35	2.07	4.00	5.02	10.06

Table 5. Leverage metric summary

	Budget 1	Budget 2(1)	Budget 2(10)	Budget 2(20)	Budget 3	Budget 4
L(AB)	0.06	0.06	0.06	0.06	0.06	0.05
L(\$)	0.07	0.08	0.09	0.08	0.08	0.07
L(NVC)	2.94	3.05	2.66	2.54	2.85	2.86

The mean annual burn probability for Scenario 2 was 0.1751, about 30 times higher than Scenario 1 (Figure 14). Mean fire size was higher in Scenario 2 by 4.3 times. These increases in burn probability and fire size result from the fact that lightning-caused fires were extinguished only by weather and thus had the opportunity to grow larger than in the Scenario 1 run.

While adopting the fire response policy in Scenario 2 would thus likely result in large increases in annual burned area in the short term, feedbacks would quickly produce limitations on area burned, since an area that burns is not able to burn again for a period of years in forest fuels.

Feedback rates (a term used here to describe the chance a fire will be limited by feedbacks in recently burned area) give an indication of how temporal feedbacks in fire suppression strategies could affect area burned over time (Figure 15). We found that for Scenario 1, within a five-year period, in 7% of cases, at least one ignition would have fallen in an area that was non-burnable due to having been burned during the previous five years (which we classified as a Type 1 feedback), resulting in a mean reduction of 89 ha or 3% of burned area (Table 7). For Scenario 2, the Type 1 encounter rate was 91%, indicating that the increased burned area can be

expected to form barriers to future fire ignition and spread in nine out of ten random five-year periods, producing an average reduction of 67,163 ha or 64% of burned area. The effect of Type 2 feedbacks (under which we assumed an area could burn only once within five years, as well as that Type 1 feedbacks are also in play) was also powerful. Type 2 feedbacks occurred in 27% of five-year periods under Scenario 1, and in 94% of random draws for Scenario 2. Commensurately, average reductions in burned area were larger: 148 ha (5%) for Scenario 1 and 100,476 ha (81%) for Scenario 2.

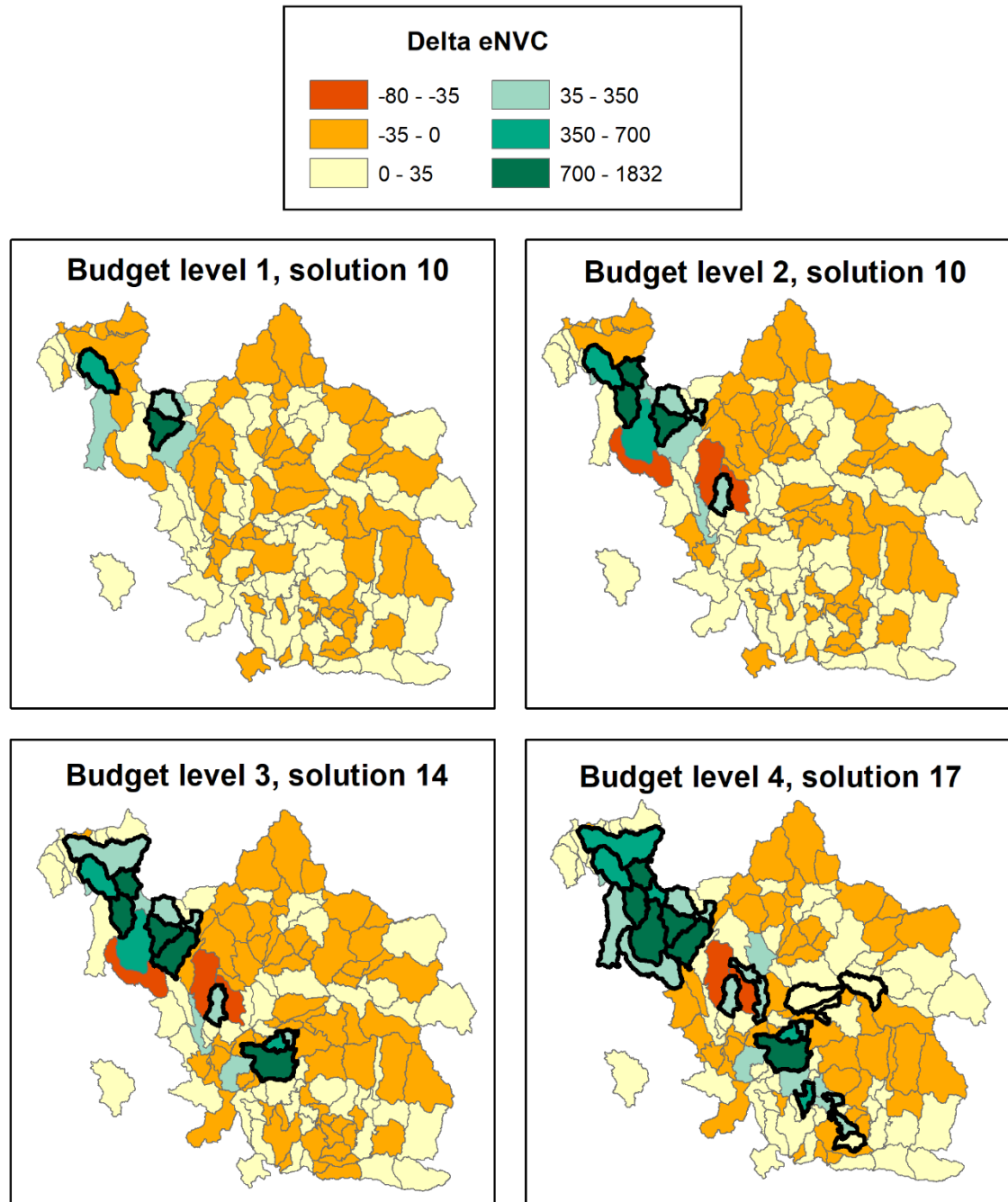


Figure 11. Net change in total POD-level eNVC under four treatment scenarios. Positive values indicate reductions in net loss. Black outlines indicate treated PODs.

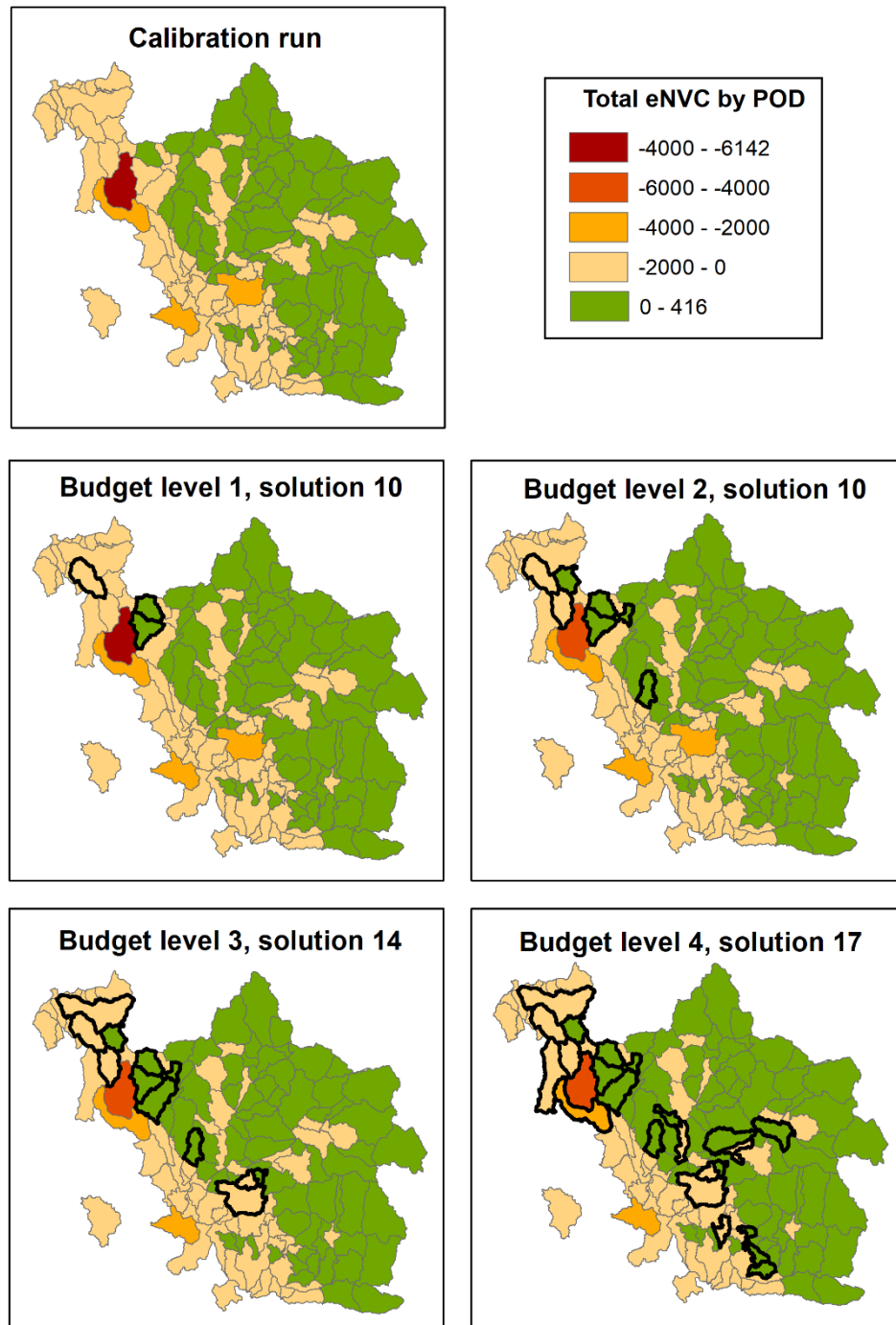


Figure 12. Total POD-level eNVC under existing conditions (calibration) landscape, as well as four treatment scenarios. Black outlines indicate treated PODs.

Table 6. Results of FSim runs, in terms of metrics used in calibration. Large fires are those that are greater than or equal to 100 ha.

Metric	Observed, all causes	Scenario 1	Scenario 2
Number of large fires	9.1	8.4	38.6
Median large-fire size (ha)	309	395	1719
Mean large-fire size (ha)	1372	1301	13,561
Mean burn probability for Sierra National Forest	0.0053	0.0048	0.1751

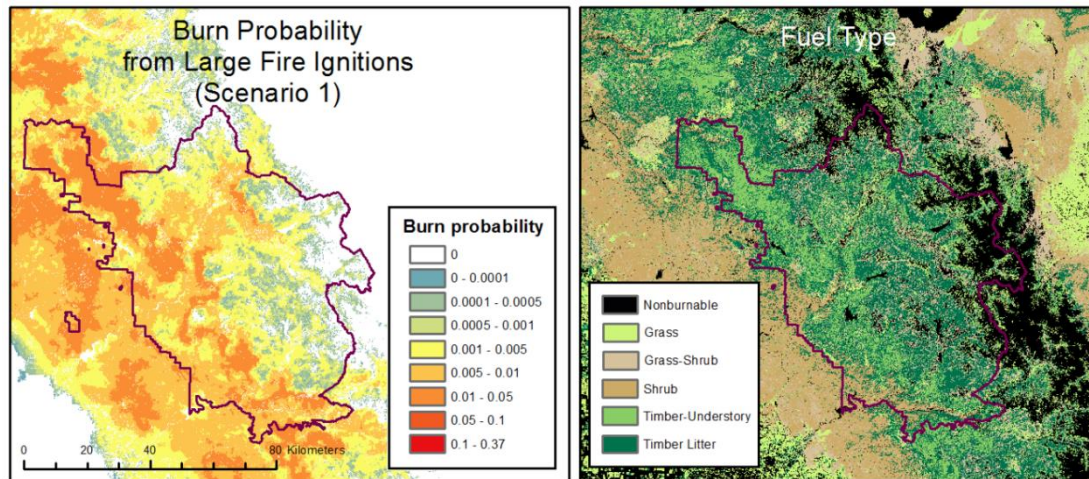


Figure 13. (a) The annualized burn probability from large fires with full suppression (Scenario 1 outputs). Burn probabilities were affected by fuel type (b), which affects fire spread rates. Note that the burn probabilities are displayed on a logarithmic scale, so that warmer colors correspond to order-of-magnitude higher burn probabilities.

If the duration over which an area is considered non-burnable is extended to ten years, the feedback effects strengthen in number and magnitude. Type 1 feedbacks occurred in 12% of random ten-year draws for Scenario 1 and would produce an average acreage reduction of 174 ha or 7% of burned area. If Type 2 feedbacks are also in play, approximately 37% of cases would be affected, with a mean acreage reduction of 289 ha or 10% of burned area. These figures are approximately double those for the five-year period. For Scenario 2, 94% of random ten-year draws had a Type 1 feedback, producing a mean acreage reduction of 83,540 ha or 78% of burned area. When Type 2 feedbacks are also included, 95% of cases were affected for a mean acreage reduction of 117,185 ha or 95% of burned area. Acreage reductions for Scenario 2 over a ten-year period are less than double those of the five-year period, as the landscape is becoming saturated by burning at higher rates and the acreage reductions are slowing as they approach toward 100%.

Therefore, while burn probabilities might increase dramatically over the short term under

Scenario 2, feedbacks can be expected to cause marked self-limitation in burned area and constrain burn probabilities and potential for large fires within a short timeframe.

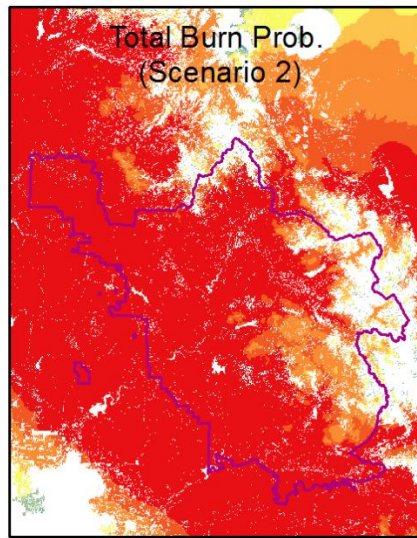


Figure 14. Annual burn probability results for Scenario 2. The burn probability scale is the same as in Figure 13a.

Conclusions (Key Findings) and Implications for Management/Policy and Future Research:

Modeling results generally confirmed all of our hypotheses, notably that fire-treatment encounters are rare (such that median suppression cost savings are zero), that treatment strategies can reduce risk and possibly expand opportunities for moderated suppression response, and that such changes in suppression response lead to feedbacks that limit burned area over time. The requisite of experiencing statistically rare events to offset upfront investments is an increasingly common theme in the fuels management literature. Here we found that under most years the benefits of a fuel treatment investment may be negligible (from the perspective of changing fire outcomes), although under extreme (1/10,000) years the investment could yield a large return in avoided costs and damages. Over time, mean annual savings can accumulate such that return on investment approaches break even in terms of financial metrics alone. On top of this, high leverage rates for risk reduction suggest the possibility for positive return, but with the caveat that treatment benefits are highly uncertain and dependent on the vagaries of fire-treatment encounters, and additionally that most benefits are accrued at the site of the treatment with offsite benefits minimal.

The primary contributions of our efforts to model alternative fire suppression responses are to introduce and illustrate a proof-of-concept modeling approach for approximating alternative fire suppression strategies, and to examine the extent to which feedbacks might produce self-limitation in burned area under different strategies. Relative to approaches that attempt to model the productivity or effectiveness of suppression actions directly, the proxy approach taken here has the advantage of being calibrated against observed fires, and we believe it is less subject to errors and assumptions resulting from knowledge gaps relating to the effectiveness of suppression actions. Due to the significant amount of computing effort and time required for the simulations, we simulated only two fire response scenarios, but we expect that

the modeling framework will be useful in simulating any number of different fire response policies in future work, including more complex response scenarios where the decision of whether to use full suppression hinges on both the fire's location and the day of year.

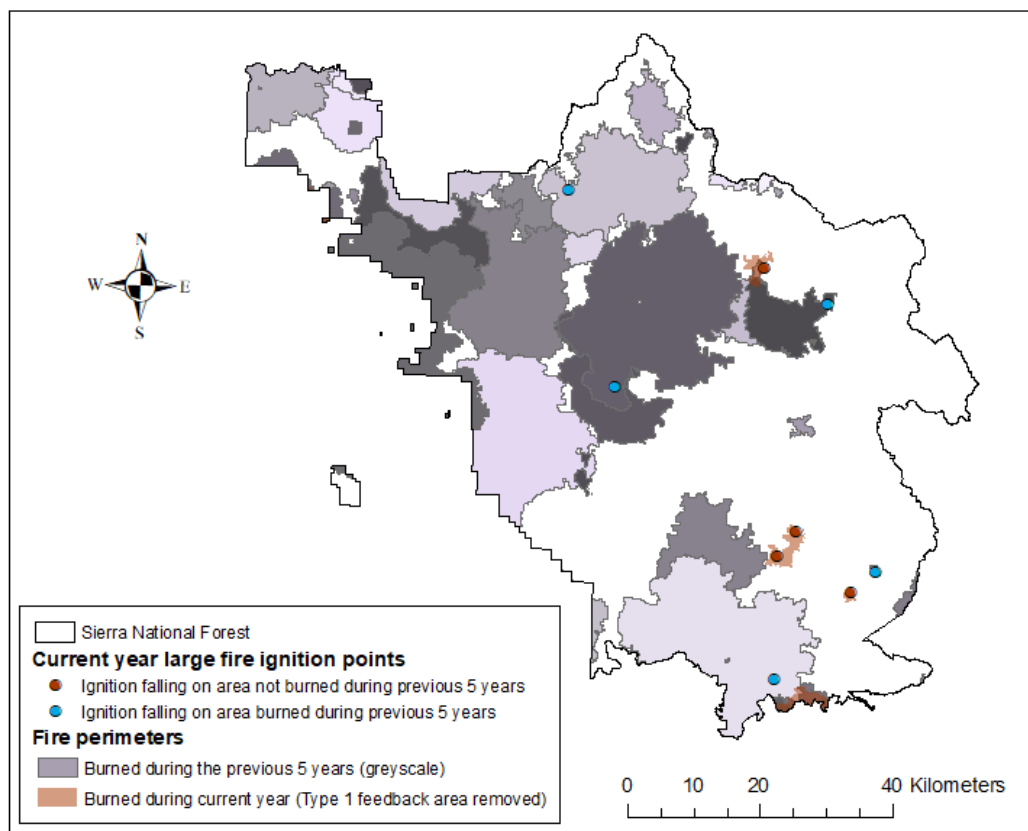


Figure 15. An illustration of the two types of encounter rates for a set of ignition locations and corresponding fire perimeters for five randomly selected model years in Scenario 2. Fire perimeters from the previous five years are displayed in greyscale. Under Type 1 assumptions, five of the nine fires would not have ignited because they fell atop an area burned during the previous five years; these ignition locations are shown in blue while other ignition locations are dark orange. Under Type 2 assumptions, the areas where the orange (current year) perimeters overlap with a grey perimeter would not have occurred, as the grey areas would remain non-burnable for five years. In this particular case, if there were no feedbacks in effect, the total area burned by large fires during the current year would have been 14,969 hectares in the Sierra Nevada National Forest. Under Type 1 assumptions, the area would have been reduced to 4,597 hectares (69% reduction). Under Type 2 assumptions, the area would have been further reduced to 2,793 hectares (81% reduction).

The value of such a modeling approach also stems from helping address the growing biophysical need in the western U.S. and other locations for more fire on the landscape in order to reduce hazard and restore forest condition (North et al 2015a, North et al 2012). Some previous work indicates that such fires that are managed for resource benefit in the Sierra Nevada are of lower severity than fires where full suppression is utilized (Meyer 2015). Whether fire managers are interested in utilizing alternative suppression approaches in pursuit of ecological goals, enhanced fire responder safety, exploring temporal feedbacks, or other concerns, we believe the general approach could have broad global applicability. Although the

scenarios we explored are broadly representative of the fire management continuum, they should not be taken as indicative of actual management policies or strategies that would necessarily be pursued by local managers. Obviously, factors like the location and susceptibility of highly valued resources and assets on the landscape will dictate where and under what conditions fire managers would realistically opt to let lightning-caused fires burn without suppression.

Table 7. Effect of feedbacks on burned area during five- and ten-year periods. NB=non-burnable duration. * Note that proportions could not be calculated when the area burned was zero, resulting in NA values (for the four scenarios, these were respectively number of NAs=2725, 2750, 468, 465).

			Scenario 1		Scenario 2	
			NB= 5 years	NB= 10 years	NB= 5 years	NB= 10 years
Without feedbacks	area burned (ha)	Median	571	529	39,153	41,793
		Mean	2,457	2,367	119,663	122,686
Type 1	% of cases affected		7	12	91	94
	avoided area burned (ha)	Median	539	467	8,919	5,493
		Mean	89	174	67,163	83,540
	avoided area burned (proportion) *	Median	0	0	71	83
		Mean	3	7	64	78
Type 2	% of cases affected		27	37	94	95
	avoided area burned (ha)	Median	0	0	30,345	39,892
		Mean	148	289	100,476	117,185
	avoided area burned (proportion) *	Median	0	0	93	99
		Mean	5	10	81	95

We leveraged our simulation approach to demonstrate that there are feedback loops that will affect annual burn probabilities, fire sizes, and number of large fires over time. While fire management strategies that limit suppression may produce markedly higher burn probabilities over the short term, the larger number and size of burned areas in this type of scenario would (depending on severity and subsequent vegetation dynamics) likely form barriers to the ignition and spread of future fires, in essence acting as fuel breaks. The feedback rates between burned areas and subsequent ignitions reported here are a first step in demonstrating the temporal dimension of alternative fire suppression strategies using our modeling framework. Compared to a full-suppression scenario, feedbacks in burned area were expected to result in larger and substantial limitations of ignitions and area burned in the scenario where lightning fires were not suppressed. Therefore, while burn probabilities would be elevated under the latter scenario in the short term, feedbacks would be likely to limit future fires somewhat, an effect documented also in observed fires (Parks et al 2015, Parks et al 2016).

The use of modeling scenarios such as those presented here can help inform land

management decisions. Our results provide further support for the use of wildland fires as a fuel treatment, in order to reduce the potential for ignition and spread of future fires, especially where the landscape may benefit from fire, or where a burned area may serve as a barrier to protect highly valued resources such as municipal watersheds (Thompson et al 2016d, Parks et al 2015, Parks et al 2016). Previous work has provided a framework to evaluate the potential benefit and loss from the next fire (Scott et al 2013); the work presented here begins to incorporate the temporal dimension of feedbacks in burned area, translating to an enhanced ability to balance tradeoffs between short- and longer-term risks.

Figure 12 may tell the most compelling story – treatment strategies can transform total POD-level risk from expected loss to expected net benefit to highly valued resources and assets. When conditions allow, managers could opportunistically use lightning-caused fires in these PODs with expected net benefits, and leverage pre-identified control features to limit fire extent within desired boundaries. That many PODs with expected net benefits are adjacent to other PODs with expected net benefits suggests that controlled burns and managed fires could expand to the scale of multiple PODs. Modeling results of fire-fire encounters and subsequent feedbacks further suggest that such fire management practices could over time provide more treated area and provide more opportunities for safe and effective fire control, as well as potential buffers to prevent growth of wildfires into PODs with expected net loss from fire.

It would be premature to call our findings authoritative or applicable across geographic areas, but we hope this project will provide tools and insights that can inform future fire and fuels management decisions. For instance, the specific slopes of curves illustrating reductions in burn probability with distance from treatment are unique to this study. But the broader point – that in-depth analyses can deconstruct how treatment strategies affect off-site hazard and risk – can and perhaps ought to be incorporated into treatment design where reducing risk outside of treated areas is an objective. The limited opportunities for mechanical treatment suggest that application of controlled burning and managed natural fire may be necessary to change broader landscape conditions, not only on this specific landscape but across dry mixed conifer forests in the Sierra Nevada region of California (North et al. 2015b).

It would be overly simplistic to suggest that our findings offer some panacea to the management challenges of the SNF. The areas where expanded fire may present the greatest benefit in terms of reduced future risk may also be the areas of highest current risk, i.e., the western flank of the SNF proximal to the wildland-urban interface. Our results do suggest however that coupling expanded fuels treatment strategies with opportunistic use of fire could yield ecosystem benefits consistent with land and resource objectives in areas distant from the wildland-urban interface. If nothing else, we hope this study generates more interest and analytical firepower brought to bear to enrich the integration of fuels management and suppression response planning.

Future Research

Future improvements and refinements could unfold in a number of ways. Three extensions relate to incorporating additional treatment prescriptions as decision variables, the resultant influence of effective treatment duration, and rates of retreatment to better capture management choices and temporal dynamics (Finney et al. 2008; Fried et al. 2016). Here we only tangentially addressed questions of time by calculating the payback period of suppression cost savings in relation to fuel treatment costs. That leverage metrics were largely consistent across the budget levels suggests we may not have simulated treating enough of the landscape to

see significant changes or economies of scale. Therefore modeling additional treatments and retreatments over time to significantly expand the footprint of treated areas may tell a more complete picture of dynamics between treatment scale and fire-treatment interactions. Adopting even longer time horizons would require modeling forest succession and accounting for the multitude of possible trajectories resulting from management and disturbance, which presents a complex computational challenge with substantial uncertainty, but may also yield important insights for policy and management (Riley and Thompson 2017; Barros et al. 2017).

Perhaps the most obvious and immediate extension is to more tightly couple fuel treatment and suppression response modeling (Thompson 2015). Here we designed treatment strategies that incorporated management units relevant to fire operations (i.e., PODs), which is but one step in enhancing the integration of fire and fuels planning. The joint design and creation of an optimal POD network through identification of potential control locations (O'Connor et al. 2017) and prioritizing treatments to create or enhance possible control locations (Ager et al. 2013) is an avenue ripe for future work. So too is leveraging our advances in modeling alternative suppression response policies, and embedding them in a broader simulation exercise that evaluates the possibly synergistic effects of alternative fuel strategies and suppression responses, including not only stopping rules but also starting rules based on factors like seasonality and location, approximating the “go/no-go” decisions around initial response to ignitions..

Lastly, there is a need to gather empirical information on actual fuels and fire management outside of the modeling domain. Future research questions that relate more directly to suppression decisions and actions could include:

- Are fire managers always aware of the location, age, and type of treatment on the landscape, and how it might affect fire behavior or enhance control opportunities?
- Do fire managers change resource ordering and suppression tactics because of this knowledge?
- In addition to changing fire intensity and extent, do treatments result in shorter incident durations?
- Can relationships between suppression costs and fuel treatments be statistically demonstrated?

We look forward to future findings from JFSP-supported work on these and other topics (e.g., 14-5-01-25, Helen Naughton PI).

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Appendix B: List of Completed/Planned Scientific/Technical Publications/Science Delivery Products:

Peer-reviewed Publications

Thompson, M., & Anderson, N. (2015). Modeling fuel treatment impacts on fire suppression cost savings: A review. *California Agriculture*, 69(3), 164-170.
Thompson, M., Riley, K., Loeffler, D., and J. Haas (2017, in review). Modeling Fuel Treatment Leverage: Encounter Rates, Risk Reduction, and Suppression Cost Impacts. *Forests*.
Riley, K.L., Thompson, M.P., Scott, J.H., and J.W. Gilbertson-Day. (2017, in review). A model-based framework to evaluate alternative wildfire suppression strategies. *Resources*
Riley, K.L. and Thompson, M.P. (2017, in preparation). Fuel treatment effects decrease rapidly with distance.

Conference Presentations

Riley, K., and M. Thompson. (2015). Uncertainty Analysis of Wildfire Modeling. 6th International Fire Ecology Congress of the Association for Fire Ecology, San Antonio, TX.
Thompson, M., Riley, K., Hand, M., and J. Scott. (2015). Improved Spatial Fire Economics Modeling. Western Forest Economists Annual Meeting, Vancouver, BC.
Riley, K.L, Thompson, M.P., and J. Scott. (2016). Modeling Alternative Fire Response Policies: Proof-of-Concept and Preliminary Results. Fire Lab Seminar Series, Missoula, MT.
Riley, K.L., Thompson, M.P., Loeffler, D., Scott, J., and J. Haas. (2016). Can Landscape Restoration and Fire Suppression Cost Savings be Achieved via Ecological Fire Response? Proof-of-concept and Preliminary Results. 3rd Southwest Fire Ecology Conference, Tucson, AZ.
Riley, K. (2017). How Might Different Wildfire Response Policies Affect the Landscape Over Time? Can We Save Money on Wildfire Suppression by Investing in Fuel Treatments and Prescribed Fire Instead? University of Montana, College of Forestry and Conservation Lecture Series, Missoula, MT.
Riley, K.L., Thompson, M.P., Haas, J., and D. Loeffler. (2017). Optimizing Fuel Treatments Based on Risk Reduction and Budget Constraints. National Cohesive Wildland Fire

- Management Strategy Workshop, Reno, NV.
- Riley, K.L., Thompson, M.P., Scott, J., and J. Gilbertson-Day. (2017). Managed Fire as a Fuel Treatment. National Cohesive Wildland Fire Management Strategy Workshop, Reno, NV.
- Thompson, M., Riley, K., Loeffler, D., and J. Haas. (2017). Fuel Treatment Leverage: Encounter Rates and Net Cost Impacts. Western Forest Economists Annual Meeting, Fort Collins, CO.