EXECUTIVE SUMMARY

The 2004 Amendment to the Sierra Nevada Forest Plan identified a coordinated system of fuel treatments distributed across the landscape as the preferred management alternative. The goals of this approach, defined as strategically placed land area treatments (SPLATs), were to modify dangerous fire behavior and improve forest health in the National Forests in the Sierra Nevada region of California. The 2004 amendment also introduced the concept of fireshed management. In concept, firesheds are analogous to watersheds but are topographic units delineated based on the behavior of a problem fire – a fire that has the greatest potential impact based on the local topography, weather, and fire history. We tested the performance of SPLATs as designed and implemented by US Forest Service in two firesheds, Last Chance in the Tahoe National Forest and Sugar Pine in the Sierra National Forest. We conducted detailed field measurements before and after treatments in order to quantity changes in forest structure and fuel loads resulting from SPLATs. To account for potential changes unrelated to forest management, a control fireshed was paired with the treated fireshed at each site. Data from the field measurements were used to parameterize fire and forest growth models. These models were then used to simulate wildfire effects on fire behavior and to explore the responses of tree growth efficiency (a measure of tree vigor) to the treatments. At Last Chance, fuel treatments distributed
across 18% of the landscape reduced the percentage of the forest exposed to damaging flame lengths from 33% (no SPLATs) to 22% (with SPLATs). The impact of SPLATs on fire behavior was less at Sugar Pine. Fire simulations for Sugar Pine showed that SPLATs completed on 29% of the area, reduced exposure to damaging flame lengths from 29% of the landscape to 25% – a modest decline of 4 percentage points. In contrast, trees in the treated fireshed at Sugar Pine nearly doubled their growth efficiency in the ten years following SPLATs while there were only minor improvements in growth efficiency following treatments at Last Chance. This dichotomy in the response to SPLATs was related to differences in the extent and intensity of the treatments applied at the two sites as well as ecological and land use variations. The treated fireshed at Sugar Pine supported a mixed conifer forest that was more crowded with bigger trees but exposed to a lower initial fire hazard. Nevertheless, in aggregate our results support the promise of SPLATs. Coordinated treatments across part of the landscape can help minimize the hazards posed by severe fires and at the same time meet forest health objectives.
INTRODUCTION

Overview

A century of forest and fire management in the Sierra Nevada has resulted in a sharp decrease in species richness and a dramatic change in the structure of the Sierran forest (Minnich et al. 1995, Collins et al. 2011, Taylor et al. 2014). Abundances of shade-tolerant white fir (Abies concolor), Douglas-fir (Pseudotsuga menziesii var. menziesii) and incense-cedar (Calocedrus decurrens) have increased at the expense of the shade-intolerant ponderosa pine (Pinus ponderosa) and sugar pine (Pinus lambertiana) which require canopy gaps to regenerate successfully (York et al. 2011). Under an intact disturbance regime these canopy gaps would have been created by small patches of tree mortality resulting from fire, insects, and disease; these gaps are largely absent in contemporary fire-suppressed forests (Larson and Churchill 2012, Lydersen et al. 2014, Fry et al. 2014). Dense stands of young white fir, Douglas-fir, and incense-cedar are characterized by increased numbers of small diameter trees and increased canopy cover (Minnich et al. 1995, McIntyre et al. 2015). In some particularly vulnerable communities, these changes may have already increased the likelihood of uncharacteristic impacts from fire and insects (Brown et al. 2008, Naficy et al. 2010, Taylor et al. 2014).

The regional assessment of current forest conditions in the 2004 Sierra Nevada Forest Plan Amendment (USFS 2004) acknowledged how these changes in forest structure and composition associated with past land management practices have exacerbated the risk of severe fire (Biswell 1989, van Wagendonk 1998) and made modifying wildland fire behavior the management priority. The preferred alternative identified in the 2004 Plan amendment (USFS 2004) was to apply strategically placed area treatments (SPLATs). SPLATs consist of discrete treatment units arranged in a strategic pattern across a landscape, which collectively slow fire
spread and moderate fire effects across the landscape (Finney 2001). Simulations have shown that with as little as 30% of the area in SPLATs, fire risk can be decreased for the entire landscape. The landscape unit of management is defined as a fireshed. In concept, firesheds are analogous to watersheds but are topographic units delineated based on the behavior of a problem fire – a fire that has the greatest potential impact based on the local topography, weather, and fire history. The size of firesheds can vary but they need to be sufficiently large to assess the effectiveness of fuel treatments and encompass characteristic fire sizes for a given area (Bahro et al. 2007).

Despite the promise of SPLATs, there are only a few spatially relevant, fully implemented landscape treatment projects in mixed conifer forests in the Sierra Nevada from which to evaluate and guide management decisions (see Moghaddas et al. 2010). The 2004 Amendment (USFS 2004) recognizes this uncertainty as well as the concern for how SPLATs might affect other forest resources. On one hand, SPLATs may provide important co-benefits. For example, the preferred alternative noted the specific objectives of improving tree vigor and overall forest health that might accrue from reducing tree density. This concern over the health of the Sierran forests expressed by the federal land managers is shared by the state (FRAP 2003) as well as the cause, namely increased competition in the more crowded stands. More recent evidence has linked rising tree morbidity and mortality in Sierran forests with worsening climatic water deficits (van Mantgem and Stephenson 2007), continued exposure to chronic air pollution (Panek et al. 2013), and greater susceptibility to beetle kill (Hicke et al. 2013). On the other hand, SPLATs may degrade habitat for wildlife species dependent on attributes in late-seral forests (Stephens et al. 2014a), increase sediment yields to streams, or lower water quality.
The Sierra Nevada Adaptive Management Project (SNAMP) was formed to address the uncertainty regarding the efficacy of SPLATs in modifying fire behavior and concern regarding potential impacts on wildlife and water resources. Moreover, given the history of debate over land and resource management in the Sierra Nevada, SNAMP followed a specific mandate not only to engage stakeholders and promote active public participation but also to study the adaptive management process itself (Chapter 1). In this report, we address two objectives at the heart of the 2004 Amendment (USFS 2004):

1) What is the effect of SPLATS on wildland fire behavior?
2) Do SPLATs improve forest ecosystem health?

**Background**

**Fire.** Recent research has demonstrated an increased proportion of high-severity fire in yellow pine and mixed-conifer forests the Sierra Nevada between 1984 and 2010 (Miller and Safford 2012, Miller et al. 2009). In addition, these studies demonstrated that fire sizes and annual area burned have also risen during the same period. The authors point out that these increases co-occur with rising regional temperatures and increased long-term precipitation. Westerling et al. (2006) also demonstrated increased area burned over a similar time period, which they attributed to regional increases in temperature and earlier spring snow melts. Despite these documented increases over the last few decades, California and the western United States as a whole are in what Marlon et al. (2012) described as a large “fire deficit.” This is based on reconstructed fire occurrence over the last 1,500 years using sedimentary charcoal records. Marlon et al. (2012) argue that the current divergence between climate (mainly temperature) and burning rates is unprecedented throughout their historical record. In other words, with temperatures warming as they have been over the last several decades, we would expect to see
much higher fire activity, based on historical fire-climate associations. This divergence is due to fire management practices, which, as the authors point out, may not remain effective over the long term if warming trends continue. It is likely, given increasing temperature and the precipitation patterns since the onset of fire suppression, that fire activity would have increased over the 20th century rather than decreased had fire suppression not been implemented (Skinner and Taylor 2006, Stine 1996), further exacerbating the current fire deficit.

The large wildfires that are occurring annually throughout the Sierra Nevada demonstrate the pressing need to scale up restoration efforts to larger landscapes. Yet implementing fuels treatment across an entire landscape may conflict with desired conditions or may be operationally constrained by funding, access, and land designations (e.g., wilderness areas, protected wildlife habitats, archaeological preserves, Collins et al. 2010, North et al. 2015). In response, scientists and managers have developed and refined concepts like SPLATs that do not require saturation coverage of the landscape to achieve meaningful modification of fire behavior (Ager et al. 2007, 2010; Finney 2001, 2004; Finney et al. 2007). Owing to the complexity of modeling fire and fuels treatment across landscapes (e.g., data acquisition, data processing, and model execution), fuels treatment project design is often based on local knowledge of both the project area and past fire patterns. Recent studies in the northern Sierra Nevada and southern Cascade Range suggests that these types of landscape-level fuels treatment projects (where treatment arrangement is based more on local knowledge and fairly simple fire behavior modeling rather than intensive modeling associated with an optimization approach) can be quite effective at reducing potential fire behavior at the landscape scale (Collins et al. 2011, 2013, Moghaddas et al. 2010).
Although only a few studies have explicitly modeled effectiveness of landscape fuels treatments using different proportions of treated area, there are some common findings: (1) noticeable reductions in modeled fire size, flame length, and spread rate across the landscape relative to untreated scenarios occurred with 10 percent of the landscape treated, but the 20-percent treatment level appears to have the most consistent reductions in modeled fire size and behavior across multiple landscapes and scenarios (Ager et al. 2007, 2010; Finney et al. 2007; Schmidt et al. 2008); (2) increasing the proportion of area treated generally results in further reductions in fire size and behavior; however, the rate of reduction diminishes more rapidly when more than 20 percent of the landscape is treated (Ager et al. 2007, Finney et al. 2007); (3) random placement of treatments requires substantially greater proportions of the landscape to be treated compared to optimized or regular treatment placement (Finney et al. 2007, Schmidt et al. 2008); however, Finney et al. (2007) noted that the relative improvement of optimized treatment placement breaks down when larger proportions of the landscape (about 40 to 50 percent) are excluded from treatment because of land management constraints that limit treatment activities. It should be emphasized that this is not to preclude treating more than 20 percent of a landscape to achieve restoration, resilience, or other resource objectives. These studies suggest that when beginning to deal with fire hazard in a landscape, the initial objective would be to strategically reduce fire hazard on between 10 and 20 percent of the area to effectively limit the ability of uncharacteristically high-intensity fire to easily move across the landscape. This would buy time to allow restoration activities to progress in the greater landscape (North et al. 2015).

Forest health. The terms “healthy forest” and “forest health” are used often in natural resources, yet rarely are they qualified or standardized. The confusion surrounding the term
Forest health is understandable, as there is no single, universally accepted definition. However, there are some recurring themes in the literature that create a basis for understanding.

Forest health is not exclusively a scientific concept (Kimmins 1997, Patel 1999, Sulak and Huntsinger 2012). Forest health is often defined by the social, cultural or economic values of a specific audience. For example, those with an interest in forest products and sustained local economies may define forest health as a sustainable, actively managed forest that is free of disease, with a diversity of tree species for future product markets (Lankford and Craig 1994).

Indeed forest pathologists typically consider health to mean the extent and virulence of tree disease present in a forest whether it is timberlands or wildlands (Pautasso et al. 2014). This definition is largely concerned with trees and trees alone. However, an audience interested in maintaining vigorous wildlife populations may insist that the definition be expanded beyond tree health to include the capacity of a forest to maintain viable populations of native species and retain biodiversity of flora and fauna (Dellasalla et al. 1995). The first definition measures disease and species diversity of trees, and the second measures wildlife populations. Both definitions of the “forest health” may mean opposite management regimes. Ultimately, forest health becomes a social construct, defined not by an inherent, “scientifically correct” state (Warren 2007) but by variables society considers most important (Sulak and Huntsinger 2012).

Many definitions of forest health fall under the general term “utilitarian”: a forest is healthy if its condition does not threaten management objectives, current or future (Kolb et al. 1994). While it is easy to diagnose an unhealthy forest under this definition (i.e., a forest is threatening management objectives), the concept can suffer from its own circular logic, where a “forest health” is defined by meeting management objectives, yet “forest health” is the management objective.
In contrast with anthropocentric utilitarian definitions, forest health has also been defined by specific types and rates of ecological processes (e.g., Tierney et al. 2009) or by the presence of specific indicators (Woodall et al. 2011). Unfortunately, these definitions come with their own set of management problems; quantitative rates and data are not widely available for many ecosystems (Kolb et al. 1994), and there is no gold standard for all rates and processes. Indicators are multifaceted and can provide conflicting information. The challenge then becomes how to integrate multiple lines of information to assess health. Using historical rates and patterns is also tricky. Changing climate and land uses by humans make the selection of the desired parameters difficult, and even if parameters were chosen, it is unlikely that our knowledge of past ecosystem processes is sufficient to design a management regime (Wagner et al. 2000).

Often in the literature, a forest is considered healthy if is resilient or sustainable. Under this guise, a healthy forest is “one that is resilient to change” (Joseph et al. 1991, EPA 2015); “resistant to catastrophic change and/or ability to recover after catastrophe” (Kolb et al. 1994) and has “sustained ecosystem functioning” (Wagner et al. 2000). This definition is also troublesome because resilience is very difficult to measure. The resilience of a forest remains a relative unknown until exposure to disturbance or stress.

The concept of “forest health” is difficult to apply to landscape-level processes because its origins lie at the individual level. Ecosystem health is a metaphor borrowed from human health (Kimmins 1997) and is problematic when applied to whole ecosystems, just as human health is difficult to apply to whole populations (Raffa et al. 2009). A dead or dying single tree is inherently unhealthy, but a dead or dying stand is more difficult to diagnose. Kolb et al. (1994) define an unhealthy stand as only unhealthy if the rate of mortality exceeds the capacity for stand replacement, but this may not necessarily apply at a forest or landscape level.
For SNAMP project, we have built on the idea that individual tree growth and survivorship are fundamental components of forest health. While this focus on tree vigor recognizes the foundational role of trees in forests (Ellison et al. 2005), it does not encompass the term’s broader usage (Sulak and Huntsinger 2012). Thus in addition to measuring tree vigor we also assessed the impact of SPLATs on forest structure and species composition.

Adaptive Management Experiment

SNAMP was structured as a deliberate experiment in adaptive management (Chapter 1). Thus the design and implementation of the SPLATs on the landscape was left entirely to the US Forest Service. We measured forest and fuel characteristics before and after treatments. These data serve as the basis for both direct comparisons as well as input for the necessary simulation experiments of fire behavior.

METHODS

Site Description

Last Chance, the northern study area (Figure 1) is defined by the boundaries of four adjoining watersheds. The treatment fireshed consists of the two central watersheds: Deep Canyon and Grouse Creek. We used the two immediately adjacent watersheds as the control (Screwauger Canyon and Peavine Creek). In total, the study site encompasses an area 38.4 mi² (99.5 km²), with elevation ranging from 2,625 ft (800 m) in the southwest to almost 7,218 ft (2,200 m) in the northeast portion of the study area. Soils are moderately deep, well-drained Inceptisols with a gravelly loam texture. The Crozier and Hurlbut soil series that are most common at Last Chance are derived from andesite and metasedimentary parent material (NRCS
The climate is Mediterranean with a predominance of winter precipitation, a majority of which is snow, averaging 46.5 in/yr (1,182 mm/year). Mean monthly temperatures are 37.4 °F (3°C) in January and 69.8 °F (21°C) in July (1990–2008; Hell Hole Remote Automated Weather Station).

Sugar Pine, the southern study area (Figure 2) is located in central Sierra Nevada, approximately 124 mi (200 km) south of Last Chance. Encompassing approximately 12.9 mi² (33.6 km²), elevation at Sugar Pine ranges from 3.936 ft (1,200 m) in the southwest to almost 7,216 ft (2,200 m) in the northeast portion of the study area at Speckerman Mountain. The deep, well-drained soils at Sugar Pine developed from weathered granodiorite. Holland family soils (Inceptisols) with a sandy loam texture are most common (NRSC 2015). The climate is also Mediterranean with snow dominating the 42.9 in/yr of precipitation (1,091 mm/year). Mean monthly temperatures are 35.6 °F (2 °C) in January and 64.4 °F (18°C) in July (1941-2002; Yosemite National Park).

Vegetation at Last Chance is dominated by the Sierra Nevada mixed conifer forest. White fir (Abies concolor) and Douglas-fir (Pseudotsuga menziesii) are the two most abundant species but incense cedar (Calocedrus decurrens), sugar pine (Pinus lambertiana), ponderosa pine (Pinus ponderosa), and California black oak (Quercus kelloggii) appear as codominants at variable densities. Stands of montane chaparral dominated by manzanita (Arctostaphylos spp) are interspersed throughout.

The mixed conifer forest is also the most common vegetation type at Sugar Pine but species composition differs from Last Chance in that there is no Douglas-fir, and the Nelder Grove watershed contains a small grove of giant sequoia (Sequoiadendron giganteum). In addition to black oak and interior live oak (Quercus wislizeni), typical hardwood and shrub
species include white alder (*Alnus rhombifolia*), Pacific dogwood (*Cornus nuttallii*), mountain whitethorn (*Ceanothus cordulatus*), deerbrush (*Ceanothus integerrimus*), and greenleaf manzanita (*Arctostaphylos patula*).

Fire history, inferred from fire scars recorded in tree rings, suggests a pre-Euro-American settlement fire regime with predominantly frequent, low-severity fires occurring at regular intervals (Stephens and Collins 2004, Scholl and Taylor 2010). Based on fire scars collected on site, the median fire interval for Last Chance was 15.0 years and 11.0 years for Sugar Pine (Appendix A.1). Native American activity in the study areas was likely high before European settlement. The Nisenan Native American community once inhabited the forests of north-central Sierra Nevada. Up until 1901, the area that is now Bass Lake (approximately 5.5 mi [9 km] from the Sugar Pine watershed) was a large, lush meadow inhabited by Chuckchansi and Mono tribes. Fire was used extensively to keep the forest open, encourage herbaceous growth for game animals, and produce vegetative growth conducive to basket weaving and arrow construction (Appendix A.1).

**Field Measurements**

From a random starting point, we established forest inventory plots at 1640-ft (500-m) spacing across both study areas to characterize stand structure and record changes in conditions due to treatments (Figure 3). This core grid resulted in 328 plots in Last Chance (LC) and 127 plots in Sugar Pine (SP). In the small instrumented catchments used to measure hydrological responses, we increased the sampling effort by reducing the spacing to 820 ft (250 m) or 410 ft (125 m) between plots. To better characterize fire effects, we doubled the number of plots in a recently burned area in LC (Peavine fire) by adding plots at every 820 ft and extended the core
plot network to a site with recent fuel treatments just south of SP (Cedar Valley). As a result we have a total of 408 and 284 pre-treatment plots in LC and SP, respectively. Pre-treatment plot measurements were collected during the summer in 2007-08. In order to maximize the time since treatment, we completed the post-treatment sampling in one field season -- 2013. The consolidated field season coupled with limited access due to wildfire (the American Fire began burning on August 10, 2015 just west of LC) forced us to prioritize our sampling efforts. Thus we first re-measured the plots on the core grid followed by plots in treated areas. Our total plot sample size with both pre and post-measurements is 369 at LC and 257 at SP. For vegetation mapping and the development of fire models, we used all available plots. For quantifying forest composition and structure differences between the reference and treated firesheds, we used only the plots on the core grid.

Plots were circular with an area of 0.12 ac (0.05 ha) and were navigated to using either a Trimble GeoXH or Garmin handheld global positioning systems (GPS). We used a nested sampling methods based on tree diameter (measured at breast height (dbh, 4.5 ft or 1.37 m above the ground): Overstory trees with dbh ≥ 7.67 in (19.5 cm) were sampled on the entire plot (0.12 ac or 0.05 ha); understory trees with dbh between 2.0 – 7.67 in (5- 19.5 cm) were sampled on a random one-third "pie-slice" of the plot (0.04 ac or 167 m²); small trees with dbh < 2 in dbh (5.0 cm) were sampled with 6.6 ft (2-m) wide radial transect (0.018 ac or 76 m²). We recorded species, vigor, crown position, dbh, total height, and height to live crown base (live trees only) for overstory and understory trees. For small trees, we recorded species and dbh in 0.4 in-classes (1 cm). We tagged all live overstory trees in the plots and tracked the fate of these trees between surveys.
We sampled surface and ground fuels along three radial transects (41.4 ft or 12.62 m) in each plot. We choose the direction of the first transect at random and then placed the remaining two at ±120° angles. Using the line-intercept method (Brown 1974), duff, litter, and surface fuel depths were measured at two points along each transect. Downed woody fuels were tallied along subsets of each transect: 0–1 m (0–0.64 cm and 0.64–2.54 cm branch diameters), 1–3 m (2.54–7.62 cm), and 0–12.62 m (>7.62 cm). Fuel loads were calculated using species-specific coefficients from van Wagendonk et al. (1996, 1998), weighted by basal area for tree species recorded in the plot (Stephens 2001). On the same three transects we measured shrub species cover via line-intercept and recorded the height of the intercepted shrubs. We used a tube densitometer to estimate canopy cover. We gridded the circular plot into 25 evenly spaced points and recorded if canopy was present directly overhead at each point.

**Fuel Treatments**

Fuel treatments (Figure 3) were typical of mixed conifer forests (Agee and Skinner 2005). In general, the prescriptions called for treating approximately 25–40% of the treatment firesheds by thinning, mastication, and prescribed fire. Thinning treatments included commercial and biomass thin from below (both sites) and cable harvesting (LC only) followed by mechanical/hand piling and burning. Mastication involved the removal of both shrubs and small trees. At LC, mastication occurred primarily within 20- to 30-year-old plantations. At SP, mastication followed some thinning treatments. Prescribed fire focused on understory burning as the primary fuel reduction method (USFS 2009, USFS 2010). For a host of reasons, treatments were initially delayed and then implemented over several years (2008–2012). During the project planning process some treatments were moderated at SP due to wildlife habitat requirements. At
both sites, not all of the planned treatments were completed by 2013 when the final field
measurements were obtained. Within the LC study area, the 2008 Peavine Fire (551 ac [223 ha])
burned in August prior to our pretreatment survey. While not considered a component of our fuel
treatment network, post-burn forest structure was measured and incorporated into the landscape
forest structure. At SP, fuel treatments in Cedar Valley, the fireshed just south of our paired
firesheds (i.e., Sugar Pine and Nelder Grove, Figure 2) started in 2007. Although not part of the
experimental design, we extended our plot network into Cedar Valley and obtained pre and post-
treatment measurements. Results from Cedar Valley were used to augment our analysis of
treatment impacts on forest structure and fuel loads.

We used information from three sources to identify actual treatment area, treatment type,
and extent of change. First, changes to forest structure were obtained by repeated measurements
of the aforementioned plot network; field observers noted type of treatment. Second, Forest
Service District offices supplied GIS-based polygon files identifying treated areas. Lastly,
remotely sensed change detection maps, produced by determining areas where differences
between pre-treatment and post-treatment maps surpassed threshold values denoting structural
change (e.g. > 10% reduction in canopy cover or mean tree height), identified areas that were
potentially treated (Su et al. 2015a). Because there can be inconsistencies between agency-
generated treatment maps and actual treatment extent, and change detection maps were limited in
the ability to identify some treatment types, all three sources were required to ascertain treatment
boundaries.

Vegetation Mapping
We developed a vegetation map from our plot and remote sensing data. This map served as the base layer for the development of all landscape map layers required for fire and forest growth simulations. The map consisted of stands, or polygons, classified into vegetation types that captured gradients in tree species composition and forest structure. Classification used both multispectral aerial imagery and Lidar-derived metrics (Appendix B-Spatial in this report, Su et al. 2015b). The pretreatment forest landscape was divided into seven vegetation types at LC and four and SP (Figure 4, Figure 5). We then used the field-plot data to impute detailed vegetation attributes for each polygon (LC, n=1363; SP, n=1100), thereby obtaining the pre-treatment and post-treatment forest structure maps used in the fire and forest-growth modeling. We developed an imputation procedure to assign three field plots to each map polygon based on their similarity in “gradient space” (Ohmann and Gregory, 2002). We performed a multivariate analysis of the plot data to define the gradient space. Variables used in the imputation included treatment type, vegetation type, canopy cover, relative density of big trees, and a suite of topographic metrics. To recreate the fine-scale heterogeneity observed in the field, we identified all plots ranked in the 95th percentile in terms of similarity and then randomly assigned three of those plots to the stand. Some plots were used to populate multiple stands. Each plot contributed data to an average of 12.6 stands (range: 1-77) for LC, and 12.8 stands (range: 1-109) for SP.

Modeling Forest Dynamics

We considered four scenarios: 1) with SPLATs and with fire; 2) without SPLATs and with fire; 3) with SPLATs and without fire; and 4) without SPLAT and without fire. We used the tree list databases associated with the 2008 pre-treatment and 2013 post-treatment field plots when simulating fire and forest growth under the ‘no SPLATs’ and ‘with SPLATs’ scenarios,
respectively. The Forest Vegetation Simulator (FVS) (Dixon 2002) with the Fire and Fuels
Extension (FFE) (Reinhardt and Crookston 2003) is an integrated system of forest growth
models that can simulate a wide range of silvicultural treatments. We used the western Sierra
variant of FVS, which does not explicitly simulate establishment of new trees in the absence of
disturbance, or ingrowth. To simulate ingrowth users must input the number, species, and
frequency of establishment events. We used a random number generator to choose the actual
number of seedlings, within species-specific bounds, that established for a given stand in a given
FVS cycle (e.g., Collins et al. 2011). Additionally, we regulated seedling height growth to
simulate more realistic conditions in a mixed conifer forest. FVS generates estimates of forest
stand structure and surface fuel loads for all four scenarios, at four time steps: 1a) 2008
pretreatment (no SPLATs); 1b) 2013 initial post-treatment (with SPLATs); 2) 2018/2023 2nd
cycle (10-year); 3) 2028/2033 3rd cycle (20-year); 4) 2038/2043 4th cycle (30-year). The forest
and fuel parameter estimates from FVS were then used to create the necessary stand
structure/fuel map layers required by the fire behavior models (Finney 2006).

We retained the tree lists generated by FVS for each scenario in order to estimate leaf
area from basic inventory parameters. For each live tree, we applied a robust set of species-
specific prediction models for the dominant species at our sites (Jones et al. In review). Predicted
leaf area was based on species, dbh, height, and crown length. Individual tree leaf areas were
summed and expressed as leaf area index (LAI), measured as the projected leaf surface area
(one-sided) per unit of land surface area covered.

Fire Simulations
We employed a dual approach to model landscape-scale fire behavior (Table 1, Figure 6). For both approaches, we derived the necessary topographic inputs, slope, aspect, and elevation from the Lidar data. Stand structure layers were derived from the FVS outputs for each stand: canopy cover, canopy base height (CBH), canopy height, and canopy bulk density. First, for the fire scenarios, we used FARSITE v.4.1.005 (Finney 1998) to simulate a ‘problem’ forest fire based on the weather conditions during a recent wildfire. Farsite is a spatially explicit fire growth model that uses several topographic, forest structure, and fuel model map layers to project fire behavior parameters over a complex landscape. For wildfire weather conditions at LC, we used the 2001 Star Fire, which burned 16,838 ac (6,817 ha), including 776 ac (314 ha) on the northeast edge of the study area. Approximately 39% of this fire burned at high severity (www.mtbs.gov; accessed on 4 February 2015). For SP, we used the 2014 French Fire, which burned 13,837 ac (5,602 ha) approximately 12.5 mi (20 km) southeast of the study area (fire severity data not available). We obtained weather information from the Duncan Peak and Batterson Automated Weather Stations (RAWS) for LC and SP, respectively. We used 95th percentile fuel moistures, as these are the conditions associated with large fire growth and difficulty in control (Table 2). The simulation duration was set to allow the fire perimeter to expand through the entire study area. Crown fire using the Scott and Reinhardt (2001) method was enabled, as well as spot-fire growth with an ignition frequency of 2% and a two-minute ignition delay.

Second, for all scenarios we used command-line version of FlamMap (Finney 2006) called RANDIG to model fires across both study areas to assess temporal changes in fire risk, thereby estimating the effectiveness of the SPLAT network at mitigating simulated fire effects, treatment longevity, and forest recovery. RANDIG uses the minimum travel time method
(Finney 2002) to simulate fire spread based on a user-inputs for: number/pattern of ignitions, fire
duration, wind speed and direction, fuel moistures, topography, stand structure, and fuels. We
used the same stand structure layers as described in the first approach. In the absence of
simulated ingrowth in FVS, stand CBH increases over time in untreated stands, which occurs at a
rate that is difficult to justify ecologically, and results in an unrealistic decrease in fire risk in fire
simulations (Collins et al. 2011, 2013). Instead, we used CBH-adjusted values as follows: initial
stand CBH calculated in FVS used in 1st and 2nd cycle fire simulations, and 3rd cycle stand CBH
calculated in FVS used in 3rd and 4th cycle. For each scenario and time step we simulated 10,000
randomly placed ignitions, burning for 240 and 360 minutes for LC and SP, respectively. This
burn period duration was selected such that simulated fire sizes (for one burn period)
approximated large-spread events (daily) observed in actual fires that occurred near the study
areas (Ager et al. 2010). Given the limited number of wildfires from which to compare large
spread events, especially for Sugar Pine, our burn period calibration represents a reasonable
normative for large spread events in Sierra Nevada mixed-conifer forests (Collins et al. 2011).

For the weather information obtained from the Duncan Peak (LC) and the Batterson
RAWS (SP), we restricted the analysis period to the dominant fire season for the area (June 1 –
September 30). Observations were available from 2002 to 2009. We identified the dominant
direction and average speed of all observations at or above the 90th percentile value. This
resulted in several different dominant wind directions, each with its own wind speed and relative
frequency (based on the proportion of observations recorded at or above the 90th percentile value
for each dominant direction). We used 95th percentile fuel moistures, as these are the conditions
associated with large fire growth and difficulty in control (Table 2).
Fuel Model Selection

To assign fuel models (Scott and Burgan 2005) to the pre- and post-treatment landscapes we analyzed relationships between fuels, shrub cover, and forest structure data collected from field plots. This approach was used for post-treatment fire simulations in Collins et al. (2011), where a selection logic was developed from regression trees and fuel models were assigned in consideration of the forest characteristics. Regression trees are ideal for such an analysis because they identify break values for predictor variables that can be used to repeatedly assign fuel models to stands. Statistical fits were moderate for each site ($R^2=0.2–0.6$), but were deemed appropriate for categorizing stands into discrete fuel models (Collins et al. 2011, 2013). The chosen fuel models for each terminal point in the selection logic was based on our familiarity with the study area and fire modeling, and input from local fire/fuel managers. Table 3 summarizes the fuel models used in the pre-treatment landscape.

A different selection logic was used for treated stands based on treatment type and time since treatment, as well as average flame length and fire type (percent of stand crowning) produced through FARSITE (first modeling approach described above) for the fire scenarios. Thinned stands that had reduced surface fuels through pile burning were left in the general selection logic. Stands that were thinned followed by mastication were assigned moderate load timber-litter model. Cable-logged stands (LC only) increased activity fuels and therefore were assigned a slash blowdown model. Masticated stands were assigned a moderate load timber-understory model, increasing to a high load timber-litter model in the second cycle. Stands that were underburned followed a progression of timber-litter fuel models but with slightly lower fuel loads. In the first fire modeling approach where all stands were burned, fuel model succession followed the methods of Davis et al. (2009). Post-burn fuel model assignment would be
contingent on pre-burn fuel model, stand average flame length, and percent of the stand crowning.

Analytical Framework

To evaluate the effects of SPLATs, we used a before-after-control-impact study design (Stewart-Oaten et al. 1986). At each site, a control fireshed was paired with the treated fireshed. Measurements were made before treatments and after treatments. This framework accounts for temporal changes that are unrelated to the treatment and thus any observed differences between firesheds can be attributed to SPLATs. Formally, the impact of the treatment can be quantified as the difference in the response between sites observed over time:

\[
\text{Treatment Impact} = (\mu_{ca} - \mu_{cb}) - (\mu_{ta} - \mu_{tb})
\]

Equation 1

where \( \mu \) is the mean of the response variable; \( c \) represents the control fireshed; \( a \) the period after treatments; \( b \) the period before treatments; and \( t \) the treated fireshed. A key assumption with this approach is that in absence of SPLATs, the differences between the sites would be constant (Stewart-Oaten et al. 1986). Note on usage: To improve clarity, we describe the "before" measurements as "pre-treatment" and the "after" as "post-treatment."

Plot-based summaries of pre- and post-treatment forest structure and surface fuels were produced for both sites, separated by control (untreated) and treatment types. Forest structure variables include canopy cover, tree density, and basal area, and shrub cover. For both fire modeling approaches, outputs of flame length, fire type, and conditional burn probabilities (both overall and proportional for 20 flame length classes [0 – 10 m in 0.5-m increments]) were obtained for individual 30-m pixels, spanning the entire study areas. Conditional burn probabilities are computed by dividing the total number of times a pixel burned by the total
number of simulated fires (n=10,000). To separate out more problematic simulated fire occurrence, both from a fire effects and a fire suppression standpoint, we only performed analysis on the burn probabilities for which modeled flame lengths were > 6.6 ft (2 m). Flame lengths > 6.6 ft typically correspond with crown fire initiation and present substantial challenges for suppression efforts (NWCG 2004). We imported flame length and conditional burn probability surfaces into ArcGIS software for further data analysis. For each of the four scenarios we computed overall mean flame length, fire type (percent of stand crowning), and conditional burn probability for each stand only using those pixels within the core study areas (i.e., stands within firesheds). We compared these outputs by stand (control vs. treated by type) and fireshed (control vs. treated).

**Forest Health Assessment**

Mortality was quantified by tracking the status of all tagged trees initially assessed as live in 2007 or 2008 in the re-measured 2013 plots. Harvested and masticated trees in the treated firesheds were noted. We calculated annual mortality (with and without harvested trees) after Sheil et al. (1995). Confidence intervals for mortality by fireshed were determined by profile likelihood (Wyckoff and Clark 2000).

The impact of treatments on forest structure and species composition was also assessed at the scale of the fireshed. Specifically, we used a two-factor analysis of variance (ANOVA) to test for differential changes (Equation 1) in forest structural characteristics (e.g., tree basal area, tree density, canopy cover) between control and treated firesheds. The interaction term in the ANOVA table served as the test of the statistical significance of the treatment effect (Smith 2002).
We developed histograms of tree-size based on dbh to document potential shifts in tree-size distributions (pre- to post-treatment) at each fireshed. Changes in size class were evaluated with a distribution departure index (Menning et al. 2007). This approach uses cumulative histograms to visualize overall trends and shifts in distributions. Specifically

\[
M = \left(\frac{2}{k-1}\right) \sum_{i=1}^{k} [\left(\hat{\rho}_i - \frac{f_i}{n_f}\right)(k + 1 - i)]
\]

Equation 2

Where \(k\) is the number of size classes; \(i\) designates the size class; \(f_i\) is the density of trees in size class \(i\) of the test distribution; \(n_f\) is the total tree density in the test distribution; and \(\hat{\rho}_i\) is the relative density in size class \(i\) in the reference distribution (Menning et al. 1997). The departure index is typically reported by stating the value and the range endpoints (e.g., \(-0.10 \, [-0.4 \, to \, 1.6]\)). The range endpoints refer to the possible changes in distribution depending on the type of reference distribution used. For example, if the reference distribution is symmetrical (e.g., a normal distribution), the possible departure index values will range from \(-1\) to \(+1\). However, if the reference distribution is asymmetrical (e.g., an inverse J-distribution with many smaller trees and fewer larger trees), the possible magnitude of any changes is also asymmetric. For an inverse-J distribution, there is the potential for a greater shift to the right than the left. A test distribution that has shifted to the right of the reference distribution will always have a positive value, while one that has shifted to the left will always display a negative value. The magnitude of the index indicates how far the test distribution has shifted. To statistically evaluate tree-size shifts from pre-measurement to post-measurement, we used a randomization approach with the pre-treatment size distribution serving as the reference (Menning et al. 2007). For each realization, the reference distribution was randomly shifted up to a maximum of 10% in either direction. We obtained 1,000 realizations and the 0.025 and 0.975 percentiles from their respective departure indices. These percentiles served as 95% confidence intervals. Observed
changes that fell outside these bounds signified shifts of 10% or more in the tree-size distribution.

Tree species composition was quantified with relative basal area. The value for each species present in the fireshed was calculated as its mean relative basal area in every plot measured. Within-fireshed variance in dominance was expressed as the standard error of this mean.

Integration Analysis

An important goal of SNAMP was to provide an integrated assessment of the impacts of SPLATs not only on fire behavior but also on forest health, populations of spotted owl and Pacific fisher, water quality, and water quantity (Chapter 4). Thus we designed the four modeling scenarios described above: no fire and no SPLATs; fire and no SPLATs; no fire and SPLATs; fire and SPLATs. Initial parameters (pre-treatment and post-treatment) were defined using our field data with models extended for 30 years. In the fire scenarios, one explicit “severe” wildfire was modeled immediately after the field measurements (time = 0.1 yr). To ensure consistency, all results were reported for 10 year time intervals from Year 0 to Year 30 at the spatial scale of the fireshed. To keep the analysis succinct, each team was charged to select one informative "integration metric." For fire behavior, we used on the conditional burn probability (described above, see Fire Simulations). For forest health, we defined two different metrics: one for scenarios without simulated fire and one with simulated fire.

Tree growth has proven to be a reliable indicator of tree survivorship in these forests (Das et al. 2007. Battles et al. 2008, Collins et al. 2014) and overall a robust indicator of forest health (Tierney et al. 2009). In this context, forest health is narrowly defined in terms of the growth of
canopy-sized trees. It is an admittedly narrow definition, but forest health in all its complexity is
difficult to capture. We can measure the performance of trees. Therefore for the integration
analysis, our fundamental premise is that “healthy” trees are a necessary but not sufficient
component of a “healthy” forest. However, growth rate by itself is not an ideal measure in the
no-fire scenario because of its mutual dependence on individual traits (e.g., tree size, tree age)
and community characteristics (e.g., tree density, soil fertility, moisture regime). Waring (1983)
argued that a good index of forest health is the efficiency with which a stands grows. Growth
efficiency (GE) was defined as the increment in stand basal area produced per unit leaf area.
Specifically:

\[
\text{Growth efficiency} = \frac{\text{Basal area}_{\text{time} \, 1} - \text{Basal area}_{\text{time} \, 0}}{\text{mean}(\text{LAI}_{\text{time} \, 1}, \text{LAI}_{\text{time} \, 0})}
\]  

Equation 3

where time 0 refers to the starting conditions, time 1 refers to conditions ten years in the future,
basal area is the cross-sectional area of trees per unit area, and LAI is the leaf area index. For the
fire scenario, we used the rate of return to pre-fire basal area to quantify forest health differences
between treatment and no-treatment. Specifically for each post-fire interval, we reported the
"fraction retained" of the pre-fire (Year 0) basal area. Since the basal area response was reported
on a relative scale, we expressed growth efficiency relative to the maximum efficiency observed
for no-fire scenario.

RESULTS

Fuel Treatments and Changes in Forest Structure

Pre-treatment forest structure varied between the two sites (Table 4). In general, the
mixed conifer forests at SP had more late-seral characteristics including high basal area (242
ft²/ac), dense canopy cover (70%), and tall trees (92 ft). Compared to LC, basal area at SP was
80% greater; the canopy was a third taller; and canopy cover was 46% higher on average. The
more open structure at LC supported more trees (i.e., higher tree density) and almost double the
shrub cover (Table 4).

There were three main types of fuel reduction treatments: thinning, mastication, and
prescribed fire. In the treated fireshed at Last Chance, SPLATs occurred on 18.4% of the area;
considerably more area was treated at Sugar Pine -- 29.3% (Table 5). Thinning at LC was
separated into two types, tractor thinning and cable logging, based on harvest prescriptions and
subsequent post-treatment fuel conditions. Some tractor thinning units at SP were followed by
mastication, which removes small trees and shrubs, converting ladder fuels to surface fuels. At
the time of our re-measurement (2013) at SP, no prescribed fire treatments had been
implemented.

For all surface fuels categories, pre-treatment plot averages were higher at SP compared
to LC (Table 6, Table 7). Although treatment area was more extensive at SP (Table 5),
treatments tended to be more intensive at LC. As results, we observed greater changes in fuels
and forest structure variables (e.g., litter, woody fuels, canopy cover, tree density, and basal area)
for a given treatment type at LC (Table 6, Table 7, Figure 7). Plots in cable logging units had to
be relocated, prohibiting direct comparisons of pre- and post-treatment plot measurements. For
plots that were in masticated units, shrub cover decreased by 50% at LC and only 10-15% at SP
(Figure 7).

From 2007-08 to 2013, the mortality rate of overstory trees (dbh ≥ 7.67 in) in the control
firesheds ranged from 1.57%/yr (95%CI: 1.2 – 2.0 %/yr) at LC to 1.05%/yr (95%CI: 0.6 to
1.7%/yr) at SP (Figure 8). The implementation of SPLATs significantly increased (based on non-
overlap of 95% CI) the death rate in treatment firesheds by about 1.2 percentage points at each
site. This increase can be directly attributed to SPLATs and not background differences between control and treatment firesheds. When harvest removals were excluded in the calculation of mortality in the treatment firesheds, we obtained values indistinguishable from controls (Figure 8).

The higher mortality rate in the treatment firesheds translated into net reductions in tree basal area and tree density in the treatment firesheds (Table 8, Table 9). For both basal area and density, the magnitude of forest structural changes was smaller in the control firesheds than in the treatment firesheds. At LC, the treatments led to an approximate 10% net decrease in tree basal area and an 11% decrease in total (overstory + understory) tree density (Table 8). The emphasis on mastication treatments at SP was evident. The largest changes related to SPLATs at SP were a 15% net reduction in understory tree density and a 35% reduction in shrub cover (Table 9). Canopy cover and big tree density (defined as trees that serve as critical habitat elements for spotted owl and Pacific fisher, Chapter 4) barely changed between control and treatment firesheds at either site (Table 8, Table 9).

It is important to note that despite the documented treatment effects at the plot and fireshed level, none of the treatment impacts (Equation 1) reported in Table 8 and Table 9 were statistically significant (p ≤ 0.05) based on test of the interaction term in the full-factorial analysis of variance (Smith 2002). In other words, we did not detect a SPLATs effect on forest structure in the treated firesheds compared to the changes with time in the control firesheds. At the standard of p ≤ 0.1 level, treatment impacts on shrub cover at SP were significant.

Forest Health
There were no changes in tree size distribution in pre-to-post treatment greater than 10% in any of the firesheds. At all sites, tree density declined exponentially with size class (Figure 9, Figure 10). The largest shift from this reverse-J shaped distribution was observed in the control fireshed at LC (Fig 9A). The post-treatment size distribution is less concentrated in the small diameter classes that the pre-treatment distribution. Such a shift results in a departure index (M) = 0.30 [min-max: -0.36; 1.64]. However this move toward a more uniform size distribution was still within the 95% CI of a 10% change: M (95%CI) = -0.14; 0.37.

All the firesheds were dominated by tree species representative of the mixed conifer forest (Fites-Kaufman et al. 2007). While there was variation in species dominance between LC and SP and between control and treatment firesheds (Figure 11, Figure 12), implementation of SPLATs resulted in only modest changes in composition. At LC, the largest shift related to treatments was a 14% decrease in white fir (ABCO) with corresponding increases of 16% in ponderosa pine (PIPO) and 12% in sugar pine (PILA) (Figure 11). At SP, the fuel treatments reduced the relative basal area of the most dominant species in the fireshed -- incense-cedar (CADE) -- by 7% (Figure 12). White fir and black oak (QUKE) both increased by 9%.

Fire Simulations

Despite similarities in weather and fuel moisture conditions (Table 2) and fuel model assignments (Table 3) used in the fire modeling, overall fire behavior tended to be higher at LC compared to SP. Differences are partly due to forest structure attributes; for example, average shrub cover and small tree density were higher at LC compared to SP (Table 4, Figure 7, Figure 9, Figure 10). Farsite fire modeling showed that most treatments reduced flame length and fire type not only within the treated units (Figure 13), but also across the study areas (Figure 14). The
largest decrease in average flame length was within prescribed fire (LC only) and thinning followed by mastication (SP only) treatment units. Cable logging at LC left activity fuels on site (Table 6), which resulted in a slash-blowdown fuel model being assigned, and consequently had higher post-treatment flame lengths and crowning. To estimate potential offsite effects from treatments we extracted Farsite output pixel values within a 1,640 ft (500 m) buffer area outside treatment boundaries. There was a decrease of 23% and 44% in average flame length at LC and SP, respectively. Treatments were effective at decreasing the proportion of stand crowning in the buffer area by 51% at LC but not at SP (decrease of 1%).

Similarly, overall conditional burn probability (CBP; fire occurring with flame lengths > 6.6 ft) tended to be higher at LC (Figure 15) compared to SP (Figure 16). This was also reflected in the average fire size for either treatment scenario from the wildfire simulations (Year 0 in Figure 17). Topography and dominant wind direction influenced fire spread resulting in higher CBPs on the west side of the study area at LC and on the east side at SP.

There was a low to moderate decrease in hazardous fire potential (flame lengths > 6.6 ft) for the treatment fireshed relative to the control fireshed (Table 10). However, the effect of time (i.e., pre- to post-treatment changes in the control fireshed) was mixed; with decreases in both fire metrics at LC but only one at SP. Thus the treatment impact (µ) on hazardous fire potential varied with a greater reduction in the extent of the fireshed with flame lengths > 6.6 ft obtained for SP and a larger decrease in high conditional burn probabilities for LC (Table 10).

The lower post-treatment CBP relative to the pre-treatment scenario (2008) was evident across both study sites in 2023 and 2033, returning to pre-treatment levels by 2043 (Figure 15 and 16). Patterns of forest growth derived from the FVS showed either a leveling or continuous increase in most attributes, for both treatment scenarios, up to 30 years post-treatment (Figure
However, as indicated by the fire size comparisons (pre- and post-treatment without fire scenarios), the effects of SPLATs was negligible by 2033 at SP (Year 20 in Figure 17). Incorporating effects of a wildfire and forest growth through FVS on both treatment scenarios show pronounced differences in recovery rates for most forest attributes (Figure 18, Figure 19), and therefore much different rates of change in CBP (CBP maps for fire scenarios not shown, see Figure 17). Following 30 years of forest growth in the fire scenario, the recovery towards pre-treatment averages was higher for the treatment scenario.

Integration

Pre-treatment crown fire potential was much higher at LC (Figure 20A) compared to SP (Figure 20B) in the treatment fire shed. The effect of SPLATs on CBP is evident at Year 0 (no fire scenario, blue bars in Figure 20), a 28% and 34% decrease at LC and SP, respectively. This difference wanes over time to only 2-4% by Year 30. Following essentially a zero CBP for either scenario immediately following simulated fire (red bars in Year 10), by Year 20 the recovery in CBP towards initial values (blue bars in Year 0) for the treatment scenario (light red bar) reached 67% at LC and 96% at SP. For the no treatment scenarios at Year 20 (stripe red bar) the recovery was slower, reaching 44% and 72% at LC and SP, respectively.

Overall the modeling results show consistent improvements in forest health with SPLATs. At both sites, a higher fraction of the pre-treatment basal area was retained (red bars) with SPLATs when there was a simulated fire (Figure 21). The treatment effect was greater at LC (Figure 21A). In Year 10 at LC, SPLATs reduced overall losses due to fire from 52% (no SPLATs, 0.48 fraction retained) to only 34% (with SPLATs, 0.66 fraction retained). As the forest grew, these differences were maintained through Year 30 (Figure 21A). In contrast, under
the no-fire scenario, SPLATs improved growth efficiency more at SP. Between Year 0 and Year
10, growth efficiency was more than double with treatments (Figure 21B). At LC, small
increases in growth efficiencies with SPLATs only emerged 20 years after the fire (Figure 21A).
Despite the small relative improvement in growth efficiency at LC, in absolute terms trees at LC
had a much higher growth efficiency. For example at Year 10 in the untreated, no-fire scenario,
growth efficiency at LC was 7.1 ft²/ac per unit leaf area. This efficiency was almost ten times
greater than the rate at SP -- 0.8 ft²/ac per unit leaf area. Apparently the relatively small changes
in density and canopy cover associated with SPLATs lead to disproportionately large
improvements in growth efficiency at the site that started with more basal area and higher
canopy cover (Table 4).

DISCUSSION

Response to SPLATS

Our results demonstrate that SPLAT networks as implemented according to the Sierra
Nevada Forest Plan Amendment (USFS 2004) does reduce the risk and effects of
uncharacteristically severe fire. This conclusion is based on a fully implemented treatment
project, with a detailed inventory plot network, incorporating simulated wildfire effects to model
fire behavior and forest growth. Comparable studies of SPLATs on fire behavior in fire-frequent
conifer forests support this conclusion (Ager et al. 2007, Moghaddas et al. 2010, Collins et al.
2011, 2013). Our results are also consistent with SPLAT theory (Finney 2001) in that fire
behavior was reduced not only in treated areas but also across the landscape, particularly on the
leeside of treatments (Weatherspoon and Skinner 1996, Collins et al. 2013). Fuel treatments that
targeted both ladder and surface fuels (e.g., thinning and prescribed fire at LC, thinning followed
by mastication at SP) were the most effective at reducing simulated fire behavior (Stephens et al. 2009, Moghaddas et al. 2010).

When we scaled our results via landscape imputation and simulation modeling, results suggest that SPLATs improved forest health as measured by the fraction of basal area retained (fire scenario) and growth efficiency (no-fire scenario). The increase in the fraction of basal area retained in the treated firesheds with a simulated problem fire (Figure 21) is the expected outcome given that SPLATs reduced the probability of trees being exposed to damaging flame lengths (Figure 20). In the no-fire scenario, ecological theory (e.g., Ford 1975) and forestry practice (e.g., Lemmon and Schumacher 1962) predict improved growth resulting from a reduction in tree density. Indeed we did detect absolute increases in growth. For example, at SP basal area increased in the treated fireshed at a rate of 0.89 ft\(^2\)/ac per year – a rate more than double that of the control fireshed (0.34 ft\(^2\)/ac per year). In contrast at LP, there was no treatment related increase in absolute basal area in the model results. Both LP firesheds grew fast at an average rate of 2.8 ft\(^2\)/ac per year. However by focusing on growth efficiency as the measure of tree vigor, we did see improvements realized at both sites (Figure 21). As noted by Waring (1983) and supported by Zierel (2004), the ratio of foliage extent to tree growth is a sensitive indicator of tree vigor. Thus the increase in growth efficiency at both sites implies that the trees in the treated firesheds are healthier and less susceptible to mortality agents (Waring 1985).

Fire

Based on our simulations, fuel treatment scale and intensity should have the capacity to modify landscape fire behavior at both sites for two to three decades. Last Chance has an overall higher fire risk compared to Sugar Pine as indicated by the higher fireshed-level CBP, which is
attributed to differences in forest structure--Sugar Pine has lower tree density and higher basal area and canopy base height--and management history. It appears that hazard in untreated areas continues to increase (see Collins et al. 2013), which is also demonstrated empirically at the stand-level by Stephens et al. (2012). This increased hazard in untreated areas over time may reduce the overall effectiveness of the fuel treatment network. Although we do not model it, maintenance treatments that would reduce surface fuels, namely prescribed fire, would probably extend treatment longevity across both landscapes. This is especially true considering most of the treatments focused on reducing ladder fuels, resulting in augmented surface fuels or a negligible change compared to pretreatment fuel conditions.

One of the main limitations in evaluating the effectiveness of landscape fuel treatments is the reliance on simulated fire behavior. Recent studies have been critical of commonly used fire behavior modeling techniques (Alexander and Cruz, 2013). In particular, these and other studies (Hall and Burke, 2006) have noted a general under prediction of crown fire. Characterization of surface and ladder fuels, represented as surface fuel models and canopy base height in commonly used modeling software, are the most influential inputs determining predicted fire behavior (Hall and Burke, 2006). In addition to their importance in capturing static assessments of altered fuel conditions in treated areas (e.g., Moghaddas et al., 2010), surface fuel models and canopy base height are essential for dynamic characterizations of changing surface and ladder fuels over time as well (e.g., Seli et al., 2008; Collins et al., 2011, 2013). Despite the importance of these two input variables, little work has been done to analyze the sensitivity of landscape fire behavior predictions, thus assessments of landscape fuel treatment effectiveness, to changes in these two variables. Furthermore, the coupling of forest dynamics models with landscape-scale fire behavior models is being implemented operationally in forest planning (e.g., Collins et al.,
Our findings provide guidance in the use of these models, which potentially improve planning outcomes and management on-the-ground.

Our previous research showed that stand canopy base heights (CBH), when projected using the forest dynamics models in FVS, increased considerably over time in untreated stands (Collins et al. 2011). This occurs at a rate that is difficult to justify ecologically, especially given the large proportion of shade-tolerant species present in many stands. Since predictions of hazardous fire potential are sensitive to CBH, modifications have been made by manipulating regeneration ingrowth levels (see Collins et al. 2011, 2013). For this study, in addition to ingrowth levels used in Collins et al. (2011), we modified the default CBH in FVS by using the FVS output from the previous cycles, thereby slowing the rate of change. For fire scenarios we only modified the last cycle (2043) by using CBH values from the previous cycle (2033). While CBH still increased over time, this resulted in a more stabilized, realistic change in CBP over time.

It is likely that the fuel model selection logic we developed had an impact on conditional burn probability and fire size outputs over the simulated duration. Our assumptions that thinned and burned stands progressed from moderate-load conifer litter to high-load conifer litter surface fuel models and, by the final cycle, entered into the untreated selection logic may or may not represent realistic fuel recovery (Collins et al. 2011). Our fuel model succession logic was aided by Davis et al. (2009), in which transitions from one fuel model to the next were based on both fire severity and time since fire. Very little research has been done in this area, and more empirical studies of fuel recovery after wildfires, prescribed fires, and mechanical fuel treatments are needed to form robust methodologies for dynamically assigning fuel models in long-term simulation studies.
Finally, a source of error in our study is the use of a stand-level model (FVS-FFE) to generate fire behavior modeling inputs across our study landscape. Our approach used a base vegetation map to delineate stands, with vegetation and fuel data from over 600 field plots in an attempt to capture the diverse vegetation conditions across our large study areas, allowing for a more detailed quantification of vegetation structure and fuels, which are then simulated independently for the study duration. Aggregating stands to create the continuous vegetation structure and fuel inputs needed to execute the fire models potentially leads to unrealistic fire behavior predictions across the landscape due to possible abrupt transitions at stand boundaries. Lidar data was used to develop a landscape vegetation map (Su et al. 2015b). Correlating surface fuel models and forest conditions is a major limiting factor in fire behavior modeling research (but see Lydersen et al. 2015). Lidar data has unlimited potential to provide quantitative information at finer spatial scales that will inevitably help improve fire behavior and fire effects modeling. Despite these potential sources of error, and the uncertainties associated with FVS-FFE projections, our analyses capture the effects of the fuel treatment network in both study sites reasonably well.

Forest health

The implementations of SPLATs at Last Chance and Sugar Pine led to only minor immediate effects on forest structure and species composition. While we did detect the post-treatment increase in overstory tree mortality due to thinning, fireshed-scale changes related to forest health were more subtle. Indeed based on the plot inventory data, none of the structural changes were statistically different from the baseline trends observed in the control firesheds (Table 8, Table 9). Several factors account for this lack of structural change. The management
priorities at both sites focused on reducing surface and ladder fuels with explicit goals to retain
large trees and maintain canopy cover (USFS 2009, 2010). Thus treatment impacts were greatest
for understory tree density and shrub cover with minimal shifts in canopy cover and big tree
density (Table 8, Table 9). Also only a fraction of the landscape was treated. Thus the majority
of plots received no treatment (Table 5). Finally at LC, trends in the control fireshed also seemed
to “track” management goals. For example, tree basal area and density declined between 2007/08
and 2013 in the control fireshed at LC (Table 8). In the case of understory trees, the decrease was
substantial (24%) and statistically significant (t-test, p <0.05). These structural changes were also
reflected in the fire models. Both fire behavior metrics at LC declined in the control fireshed
under post-treatment conditions (Table 10). There was no obvious explanation for the observed
decrease in understory tree density aside from self-thinning dynamics in a maturing stand
(Vospernik and Sterba 2015).

Changes in tree species composition were also modest (Figure 11, Figure 12). At LC,
reducing white fir dominance while increasing the pine component was an explicit treatment
goal (USFS 2009). To some extent this target was met. Treatments at LC accounted for a decline
in the relative basal area of white fir (14%) with corresponding increases in both ponderosa and
sugar pine (Figure 11B).

Both sites identified the need to reduce stand densities in order to improve the resiliency,
growth, and vigor of the remaining trees (USFS 2009, USFS 2010). While results from the FVS
growth models support the contention that SPLATs did improve tree vigor (Figure 11), forest
growth and yield simulators like FVS struggle to predict tree mortality accurately (Hamilton
1990, Battles et al. 2008, Robards 2009). Thus ultimately the measure of success of treatments in
terms of tree vigor is to improve tree survival. This criterion is explicitly stated in the LC
environmental impact assessment (USFS 2009). Subsequent treatment impacts on tree mortality can be tracked directly by repeat measurements. In addition, Collins et al. (2014) demonstrated a promising method to measure changes in forest resilience caused by fuel treatments. In fact, Collins et al. (2014) applied growth-mortality models developed for LC as part of the SNAMP pre-treatment field campaign. The initial workplan for SNAMP envisioned a post-treatment follow-up to provide empirical support to the model results, but the abbreviated post-treatment period (1-2 years) was too short to measure the tree growth response. Thus future work should prioritize documenting the growth response in order to quantify treatment impacts on future forest vulnerability.

Summary

There were clear differences in the extent and intensity of the treatments between LC and SP (Table 5, Figure 7). SPLATs impact on fire behavior and forest health was further modified by the ecological and historical differences between the two sites. The treated fireshed at SP supported a mixed conifer forest that was more crowded with bigger trees (Table 4) but exposed to a lower initial fire hazard (Table 10). Thus there was a dichotomy in the response to SPLATs. In terms of modifying fire behavior, the impact of SPLATs was greater at LC; in terms of improving forest health, the impact was greater at SP. The longevity of the impacts differed as well. The gains in growth efficiency were maintained through time while the reductions in flame lengths dissipated with time (Figure 20, Figure 21).

Results from SNAMP support the promise of SPLATs. Coordinated treatments across part of the landscape can help minimize the hazards posed by severe fires and at the same time meet forest health objectives. However as noted above, to realize fully the restoration potential of
SPLATs further refinements are needed. For example, prioritizing surface and ladders fuels may be an effective means to decrease the risk of crown fire (Safford et al. 2012) while preserving structural elements (e.g., large trees and high canopy cover) important to wildlife species dependent on old-forest characteristics (Zelinski et al. 2013), it may not create gaps of sufficient size to recruit disturbance-dependent trees like ponderosa pine and sugar pine (York et al. 2011). Devising solutions that support the integrity and function of Sierra Nevada forest ecosystem will require more strategic thinking (e.g., North et al. 2009, North 2012, Stephens et al. 2014). Given the extent of the changes wrought by past management and the challenges posed by global change, the successful strategy will also need to plan for a great deal more management activity in the forest (North et al. 2015).
REFERENCES


Lemmon, P. E., and F. X. Schumacher. 1962. Volume and diameter growth of ponderosa pine trees as influenced by site index, density, age, and size. Forest Science: 236-249.


Scott, J.H., and E.D. Reinhardt. 2001. Assessing crown fire potential by linking models of

with Rothermel's surface fire spread model. USDA For. Serv. Gen. Tech. Rep. RMRS-GTR-
153. 72 p.

P. 27-39 in Proc. of conf. on Third Forest Vegetation Simulator Conference, Havis, R.N., and

Sheil, D., D. F. Burslem, and D. Alder. 1995. The interpretation and misinterpretation of

Wagetendonk, J. Fites-Kaufman, A.E. Thode (Eds.), Fire in California's Ecosystems.


Sierra Nevada at multiple spatial scales. Northwest Science 78: 12-23.

Stephens, S.L., R.E. Martin, and N.D. Clinton. 2007. Prehistoric fire area and emissions from
California's forests, woodlands, shrublands and grasslands. Forest Ecology and Management
251: 205-216.


Woodall, C.W., M.C. Amacher, W.A. Bechtold et al. 2011. Status and future of the forest health indicators program of the USA. Environmental Monitoring and Assessment 177: 419-436.


Table 1. Overview of the approach for landscape-scale fire behavior simulations.

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<td></td>
<td></td>
<td>No SPLATs/Fire: modeled forest conditions in 2018(10-yr) following modeled wildfire (Farsite), 2028 (20-yr), and 2038 (30-yr)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>SPLATs/No Fire: 2013 post-treatment (0-yr), modeled forest conditions in 2023 (10-yr), 2033 (20-yr), and 2043 (30-yr)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>SPLATs/Fire: modeled forest conditions in 2023 (10-yr) following modeled wildfire (Farsite), 2033 (20-yr), and 2043 (30-yr)</td>
<td></td>
</tr>
</tbody>
</table>
Table 2. Weather parameters for fire simulations using Farsite and RANDIG. We used 90th percentile and above winds (RANDIG only) and the 95th percentile fuel moistures (both simulations) for the predominant fire season in the area (June 1–September 30) based on data from one or more RAWS data near study sites.

<table>
<thead>
<tr>
<th></th>
<th>Last Chance</th>
<th>Sugar Pine</th>
</tr>
</thead>
<tbody>
<tr>
<td>Temperature (°F)</td>
<td>54-93</td>
<td>59-99</td>
</tr>
<tr>
<td>Relative Humidity (%)</td>
<td>11-54</td>
<td>9-68</td>
</tr>
<tr>
<td>Wind (mph)</td>
<td>6.3 (3-13.5)</td>
<td>10 (3-20)</td>
</tr>
<tr>
<td>Wind direction</td>
<td>S-SW</td>
<td>SE, W</td>
</tr>
<tr>
<td>Fuel Moisture (%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1-hr</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>10-hr</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>100-hr</td>
<td>5</td>
<td>6</td>
</tr>
<tr>
<td>Live herbaceous</td>
<td>30</td>
<td>35</td>
</tr>
<tr>
<td>Live woody</td>
<td>60</td>
<td>65</td>
</tr>
</tbody>
</table>
Table 3. Pretreatment fuel model assignments (Scott and Burgan 2005) and their proportion throughout both study areas. Fuel model selection logic was based on multiple regression tree analyses using stand-level data for dependent variables (shrub cover and fuel loads by category) and independent forest structure variables summarized using FVS.

<table>
<thead>
<tr>
<th>Fuel model</th>
<th>Description of stands with fuel model assigned</th>
<th>Last Chance</th>
<th>Sugar Pine</th>
</tr>
</thead>
<tbody>
<tr>
<td>SH3 (143)</td>
<td>Low basal area, low canopy cover, low stature shrub dominated fuels</td>
<td>0.155</td>
<td>-</td>
</tr>
<tr>
<td>SH5 (145)</td>
<td>Low basal area, low canopy cover, high stature shrub dominated fuels</td>
<td>0.054</td>
<td>0.044</td>
</tr>
<tr>
<td>TU2 (162)</td>
<td>Low basal area, high canopy cover</td>
<td>0.154</td>
<td>0.135</td>
</tr>
<tr>
<td>TU5 (165)</td>
<td>Moderate to high basal area, high tree density, moderate fuel load dominated by shrub and forest litter</td>
<td>0.318</td>
<td>0.451</td>
</tr>
<tr>
<td>TL3 (183)</td>
<td>Peavine Fire (2008) area</td>
<td>0.014</td>
<td>-</td>
</tr>
<tr>
<td>TL5 (185)</td>
<td>Low basal area, low canopy cover, moderate fuel load with coarse fuels present</td>
<td>-</td>
<td>.044</td>
</tr>
<tr>
<td>TL9 (189)</td>
<td>Moderate to high basal area, moderate to low tree density, moderate to low site productivity</td>
<td>0.042</td>
<td>.067</td>
</tr>
<tr>
<td>SB3 (203)</td>
<td>Moderate to high basal area, moderate to low tree density, high site productivity, moderate fuel load with coarse fuels present</td>
<td>0.263</td>
<td>0.26</td>
</tr>
</tbody>
</table>
Table 4. Pre-treatment forest structure at the two research sites. Results based on pre-treatment measurements were made in 2007 and 2008. Only plots on the core sampling grid were included. Basal area was calculated for all live trees ≥ 2 in diameter at breast height (dbh); density was calculated for live trees ≥ 2 in dbh; canopy cover was defined as tree cover ≥ 6.6 ft; Lorey height is a measure of tree height weighted by size (basal area) of the tree; shrub cover excludes cover from trees < 6.6 ft tall. Means are reported with standard errors in parentheses. Results include plots with no trees present.

<table>
<thead>
<tr>
<th>Site</th>
<th>Basal Area (ft²/ac)</th>
<th>Density (stems/ac)</th>
<th>Canopy Cover (%)</th>
<th>Lorey Height (ft)</th>
<th>Shrub Cover (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Last Chance</td>
<td>133 (5.9)</td>
<td>252 (12)</td>
<td>48 (1.9)</td>
<td>66 (1.9)</td>
<td>43 (1.5)</td>
</tr>
<tr>
<td>Sugar Pine</td>
<td>242 (11.0)</td>
<td>218 (13)</td>
<td>70 (1.8)</td>
<td>92 (0.9)</td>
<td>26 (2.8)</td>
</tr>
</tbody>
</table>
Table 5. Cumulative area treated (ac, [% of total watershed area]) for all treatment watersheds, separated by treatment type.

<table>
<thead>
<tr>
<th>Type</th>
<th>Last Chance</th>
<th>Sugar Pine</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mastication</td>
<td>348 (3.1)</td>
<td>217 (3.5)</td>
</tr>
<tr>
<td>Thinning</td>
<td>915 (8.3)</td>
<td>1298 (20.7)</td>
</tr>
<tr>
<td>Cable Logging</td>
<td>193 (1.7)</td>
<td>-</td>
</tr>
<tr>
<td>Thinning+Mastication</td>
<td>-</td>
<td>328 (5.2)</td>
</tr>
<tr>
<td>Prescribed burn</td>
<td>577 (5.2)</td>
<td>-</td>
</tr>
<tr>
<td>Total</td>
<td>2033 (18.4)</td>
<td>1843 (29.3)</td>
</tr>
</tbody>
</table>
**Table 6.** Average (± standard error) of surface fuels (tons ac⁻¹) and shrub cover, by treatment type, collected from plots in the Last Chance study area. C-thin, cable logging.

<table>
<thead>
<tr>
<th></th>
<th>Control</th>
<th>Burn</th>
<th>Mastication</th>
<th>Thinning</th>
<th>C-thin</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Pre-treatment</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Litter</td>
<td>7.7 (0.3)</td>
<td>8.2 (1.4)</td>
<td>3.5 (0.8)</td>
<td>11.0 (0.1)</td>
<td>4.7 (0.3)</td>
</tr>
<tr>
<td>Litter + 1-hr</td>
<td>7.9 (0.3)</td>
<td>8.4 (1.4)</td>
<td>3.6 (0.7)</td>
<td>11.2 (0.1)</td>
<td>4.9 (0.3)</td>
</tr>
<tr>
<td>1000-hr</td>
<td>10.8 (1.3)</td>
<td>2.8 (0.8)</td>
<td>1.9 (1.7)</td>
<td>13.7 (0.3)</td>
<td>17.7 (15.0)</td>
</tr>
<tr>
<td>1–1000-hr</td>
<td>13.1 (1.4)</td>
<td>5.4 (1.2)</td>
<td>3.3 (1.7)</td>
<td>16.9 (0.3)</td>
<td>22.0 (14.9)</td>
</tr>
<tr>
<td>Total</td>
<td>37.3 (1.9)</td>
<td>28.7 (4.8)</td>
<td>12.5 (2.9)</td>
<td>49.1 (0.4)</td>
<td>41.9 (13.3)</td>
</tr>
<tr>
<td>Fuel depth (in)</td>
<td>1.4 (0.1)</td>
<td>1.2 (0.1)</td>
<td>0.6 (0.2)</td>
<td>1.7 (0.0)</td>
<td>2.2 (0.0)</td>
</tr>
<tr>
<td>Shrub cover (%)</td>
<td>45.6 (1.5)</td>
<td>37.0 (9.8)</td>
<td>50.3 (9.8)</td>
<td>24.0 (0.4)</td>
<td>42.5 (4.2)</td>
</tr>
<tr>
<td>Shrub height (ft)</td>
<td>2.4 (0.1)</td>
<td>1.6 (0.4)</td>
<td>2.3 (0.4)</td>
<td>1.1 (0.0)</td>
<td>1.6 (0.4)</td>
</tr>
<tr>
<td></td>
<td>Post-treatment</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Litter</td>
<td>6.7 (0.3)</td>
<td>5.3 (1.2)</td>
<td>4.3 (0.6)</td>
<td>6.6 (0.1)</td>
<td>22.0 (17.3)</td>
</tr>
<tr>
<td>Litter + 1-hr</td>
<td>7.0 (0.3)</td>
<td>5.5 (1.2)</td>
<td>4.5 (0.6)</td>
<td>6.8 (0.1)</td>
<td>22.2 (17.4)</td>
</tr>
<tr>
<td>1000-hr</td>
<td>10.0 (1.2)</td>
<td>3.5 (1.5)</td>
<td>4.4 (3.8)</td>
<td>8.2 (0.2)</td>
<td>3.4 (1.7)</td>
</tr>
<tr>
<td>1–1000-hr</td>
<td>14.0 (2.4)</td>
<td>6.1 (1.8)</td>
<td>6.5 (3.9)</td>
<td>12.3 (0.2)</td>
<td>7.4 (1.9)</td>
</tr>
<tr>
<td>Total</td>
<td>42.2 (3.1)</td>
<td>32.6 (5.7)</td>
<td>23.2 (4.3)</td>
<td>44.9 (0.4)</td>
<td>94.0 (46.1)</td>
</tr>
<tr>
<td>Fuel depth (in)</td>
<td>1.5 (0.1)</td>
<td>1.1 (0.3)</td>
<td>1.1 (0.2)</td>
<td>1.8 (0.0)</td>
<td>4.4 (1.8)</td>
</tr>
<tr>
<td>Shrub cover (%)</td>
<td>46.5 (2.5)</td>
<td>42.4 (9.5)</td>
<td>26.9 (8.1)</td>
<td>12.3 (0.3)</td>
<td>0.7 (0.7)</td>
</tr>
<tr>
<td>Shrub height (ft)</td>
<td>2.2 (0.1)</td>
<td>1.3 (0.2)</td>
<td>1.8 (0.8)</td>
<td>0.9 (0.0)</td>
<td>0.2 (0.2)</td>
</tr>
</tbody>
</table>
Table 7. Average (± standard error) of surface fuels (tons ac⁻¹) and shrub cover, by treatment type, collected from plots in the Sugar Pine study area. Thin+Mast, thinning followed by mastication.

<table>
<thead>
<tr>
<th></th>
<th>Control</th>
<th>Mastication</th>
<th>Thinning</th>
<th>Thin+Mast</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Pre-treatment</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Litter</td>
<td>12.0 (2.1)</td>
<td>11.2 (2.7)</td>
<td>21.4 (3.0)</td>
<td>15.7 (2.3)</td>
</tr>
<tr>
<td>Litter + 1-hr</td>
<td>12.1 (2.2)</td>
<td>11.3 (2.7)</td>
<td>21.5 (3.0)</td>
<td>15.8 (2.2)</td>
</tr>
<tr>
<td>1000-hr</td>
<td>13.4 (6.2)</td>
<td>5.3 (1.8)</td>
<td>14.1 (5.4)</td>
<td>9.4 (2.3)</td>
</tr>
<tr>
<td>1–1000-hr</td>
<td>25.4 (10.4)</td>
<td>9.0 (2.7)</td>
<td>21.4 (7.2)</td>
<td>17.9 (3.8)</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>65.7 (14.2)</td>
<td>37.0 (7.0)</td>
<td>72.4 (9.9)</td>
<td>65.8 (6.9)</td>
</tr>
<tr>
<td>Fuel depth (in)</td>
<td>2.0 (0.4)</td>
<td>2.3 (0.7)</td>
<td>3.3 (0.5)</td>
<td>2.4 (0.4)</td>
</tr>
<tr>
<td>Shrub cover (%)</td>
<td>25.1 (7.4)</td>
<td>39.6 (6.9)</td>
<td>20.1 (6.9)</td>
<td>20.3 (7.1)</td>
</tr>
<tr>
<td>Shrub height (ft)</td>
<td>3.0 (0.7)</td>
<td>7.0 (0.8)</td>
<td>2.6 (0.7)</td>
<td>3.9 (0.6)</td>
</tr>
<tr>
<td><strong>Post-treatment</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Litter</td>
<td>11.0 (2.5)</td>
<td>9.6 (1.6)</td>
<td>13.1 (2.1)</td>
<td>12.2 (2.3)</td>
</tr>
<tr>
<td>Litter + 1-hr</td>
<td>11.1 (2.5)</td>
<td>9.9 (1.6)</td>
<td>13.4 (2.1)</td>
<td>12.4 (2.3)</td>
</tr>
<tr>
<td>1000-hr</td>
<td>12.6 (5.0)</td>
<td>9.1 (4.4)</td>
<td>18.0 (10.2)</td>
<td>16.5 (7.1)</td>
</tr>
<tr>
<td>1–1000-hr</td>
<td>19.0 (7.3)</td>
<td>14.5 (4.5)</td>
<td>23.8 (10.3)</td>
<td>21.0 (6.7)</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>60.9 (11.1)</td>
<td>43.8 (5.7)</td>
<td>72.5 (13.8)</td>
<td>72.1 (14.9)</td>
</tr>
<tr>
<td>Fuel depth (in)</td>
<td>2.3 (0.6)</td>
<td>2.4 (0.5)</td>
<td>3.3 (0.8)</td>
<td>4.0 (1.2)</td>
</tr>
<tr>
<td>Shrub cover (%)</td>
<td>27.6 (7.4)</td>
<td>24.1 (8.0)</td>
<td>15.8 (5.3)</td>
<td>9.1 (4.2)</td>
</tr>
<tr>
<td>Shrub height (ft)</td>
<td>2.3 (0.5)</td>
<td>2.9 (0.9)</td>
<td>1.4 (0.3)</td>
<td>2.7 (0.6)</td>
</tr>
</tbody>
</table>
Table 8. SPLATs treatment impact on forest structure at the Last Chance site. Results based on forest inventories. Pre-treatment measurements were made in 2007 and 2008. Post-treatment measurements were made in 2013. Only plots on the core sampling grid were included. Basal area was calculated for all live trees ≥ 2 in diameter at breast height (dbh); overstory density was calculated for live trees ≥ 7.67 in dbh; understory density was calculated for live trees trees ≥ 2 in dbh and < 7.67 in dbh; big tree density was calculated for live tree ≥ 28 in in dbh; canopy cover was defined as tree cover ≥ 6.6 ft. Means are reported with standard errors in parentheses. For change over time/treatment (Δ), the 95% confidence interval for the difference in means is reported in brackets. The estimate of treatment impact is the difference of means between control and treatment (Equation 2.1).

<table>
<thead>
<tr>
<th></th>
<th>Control Fireshed</th>
<th></th>
<th>Treatment Fireshed</th>
<th></th>
<th>Treatment Impact (µ)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>pre</td>
<td>post</td>
<td>Δ</td>
<td>pre</td>
<td>post</td>
</tr>
<tr>
<td>Basal area (ft²/ac)</td>
<td>138 (8)</td>
<td>134 (9)</td>
<td>-4 [-29; 20]</td>
<td>142 (8)</td>
<td>125 (8)</td>
</tr>
<tr>
<td>Overstory density (stems/ac)</td>
<td>76 (4)</td>
<td>73 (4)</td>
<td>-3 [-13; 8]</td>
<td>86 (4)</td>
<td>77 (4)</td>
</tr>
<tr>
<td>Understory density (stems/ac)</td>
<td>193 (15)</td>
<td>147 (12)</td>
<td>-46 [-84; -10]</td>
<td>241 (19)</td>
<td>169 (16)</td>
</tr>
<tr>
<td>Big tree density (stems/ac)</td>
<td>16 (1)</td>
<td>16 (1)</td>
<td>0 [-3; 4]</td>
<td>16 (1)</td>
<td>16 (1)</td>
</tr>
<tr>
<td>Canopy cover (%)</td>
<td>46 (1.7)</td>
<td>52 (1.9)</td>
<td>6 [-8.5; 1.2]</td>
<td>48 (2.1)</td>
<td>53 (2.2)</td>
</tr>
<tr>
<td>Shrub cover (%)</td>
<td>46 (2.0)</td>
<td>45 (2.0)</td>
<td>-1 [-5.1; 6.0]</td>
<td>42 (2.1)</td>
<td>45 (4.9)</td>
</tr>
</tbody>
</table>
Table 9. SPLATs treatment impact on forest structure at the Sugar Pine site. Results based on forest inventories. Pre-treatment measurements were made in 2007 and 2008. Post-treatment measurements were made in 2013. Only plots on the core sampling grid were included. Basal area was calculated for all live trees ≥ 2 in in diameter at breast height (dbh); overstory density was calculated for live trees ≥ 7.67 in dbh; understory density was calculated for live trees trees ≥ 2 in dbh and < 7.67 in dbh; big tree density was calculated for live tree ≥ 28 in in dbh; canopy cover was defined as tree cover ≥ 6.6 ft. Means are reported with standard errors in parentheses. For change over time/treatment (Δ), the 95% confidence interval for the difference in means is reported in brackets. The estimate of treatment impact is the difference of means between control and treatment (Equation 2.1).

<table>
<thead>
<tr>
<th></th>
<th>Control Fireshed</th>
<th>Treatment Fireshed</th>
<th>Impact (μ)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>pre</td>
<td>post</td>
<td>Δ</td>
</tr>
<tr>
<td>Basal area (ft²/ac)</td>
<td>265 (19)</td>
<td>267 (20)</td>
<td>2 [-53; 57]</td>
</tr>
<tr>
<td>Overstory density (stems/ac)</td>
<td>89 (7)</td>
<td>87 (7)</td>
<td>-2 [-22; 19]</td>
</tr>
<tr>
<td>Understory density (stems/ac)</td>
<td>100 (14)</td>
<td>103 (15)</td>
<td>3 [-40; 45]</td>
</tr>
<tr>
<td>Big tree density (stems/ac)</td>
<td>23 (2)</td>
<td>23 (2)</td>
<td>0 [-4; 6]</td>
</tr>
<tr>
<td>Canopy cover (%)</td>
<td>68 (2.9)</td>
<td>69 (3.1)</td>
<td>1 [-9.1; 7.6]</td>
</tr>
<tr>
<td>Shrub cover (%)</td>
<td>21 (4.1)</td>
<td>22 (4.4)</td>
<td>1 [-12.8; 10.9]</td>
</tr>
</tbody>
</table>
Table 10: Changes in fireshed-level fire behavior at both study sites. CBP, conditional burn probability for flame lengths > 6.6 ft (2 m).

<table>
<thead>
<tr>
<th>Last Chance</th>
<th>Control Fireshed</th>
<th>Treatment Fireshed</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Pre</td>
<td>Post</td>
</tr>
<tr>
<td>Percentage of fireshed with flame lengths &gt; 6.6 ft (2 m)</td>
<td>28.3</td>
<td>24.1</td>
</tr>
<tr>
<td>Percentage of fireshed with CBP &gt; 0.1</td>
<td>54.3</td>
<td>40.5</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Sugar Pine</th>
<th>Control Fireshed</th>
<th>Treatment Fireshed</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Pre</td>
<td>Post</td>
</tr>
<tr>
<td>Percentage of fireshed with flame lengths &gt; 6.6 ft (2 m)</td>
<td>25</td>
<td>28.7</td>
</tr>
<tr>
<td>Percentage of fireshed with CBP &gt; 0.1</td>
<td>67.3</td>
<td>54.3</td>
</tr>
</tbody>
</table>
Figure 1. Control (dark grey) and treatment (light grey) areas at Last Chance, SNAMP’s northern study site in the Sierra Nevada, California. Bear Trap and Frazier Creek were the headwater catchments evaluated by the Water team.
**Figure 2.** Control (dark grey) and treatment (light grey) areas at Sugar Pine, SNAMP’s southern study site in the Sierra Nevada, California. Big Sandy and Speckerman were the headwater catchments evaluated by the Water team.
Figure 3. Location of plot network and SPLATs at Last Chance (A) and Sugar Pine (B).
Figure 4. Vegetation map of Last Chance. Green polygons outline the constituent firesheds.
Figure 5. Vegetation map of Sugar Pine. Green polygons outline the research areas.
Figure 6. Flowchart of fire behavior and forest dynamics modeling.
Figure 7: Changes in forest structure by treatment type at both SNAMP study sites. Results based on pre- and post-treatment forest inventory plot measurements. Tree density and basal area are for trees with diameters > 2 in. CONT, control; MAST, mastication; THIN, thinning; C-THIN, cable logging; THIN/MAST, thinning followed by mastication; BURN, prescribed fire. *Only two plots were located in cable logging units and these had to be relocated for post-treatment measurements, prohibiting direct comparisons to pre-treatment measurements.
Figure 8. The mean annual mortality rate of overstory trees (dbh ≥ 7.67 in) in the control and treated plots at the SNAMP research sites in the Sierra Nevada, CA. Rates were calculated by tracking the fate of tagged trees between 2007-08 and 2013 inventories. Only trees in the plots from the core grid were included to ensure a representative sample. CONT refers to the control firesheds; TRT refers to the treatment firesheds; TRT-no is the mortality rate in the treatment firesheds if harvested trees are excluded from consideration. Error bars represent 95% confidence intervals.
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Figure 16. Conditional burn probabilities for which flame lengths > 2 meters at Sugar Pine. Burn probabilities are reported for pre- and post-implementation of fuel reduction treatments, as well as during 30 years of simulated forest growth. Estimates are based on 10,000 random ignitions under 90th percentile wind and fuel moisture conditions. Thin, thinning; Mast, mastication; Thin+Mast, thinning followed by mastication.
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Figure 19. Average (one standard error) forest stand attributes, by treatment type, for all four fire-treatment scenarios at Sugar Pine. Treatment scenarios are pre- and post-implementation of fuel reduction treatments reflected at Year 0, combined with (filled bars) and without (open bars) incorporating the effects of a Farsite wildfire simulation, with differences shown at Year 10. The simulated fire occurs immediately after Year 0 is measured. Attributes were calculated for each scenario during 30 years of simulated forest growth. Thin, thinning; Mast, mastication; Thin+Mast, thinning followed by mastication; CBH, canopy base height; CBD, canopy bulk density.
Figure 20. Changes in conditional burn probability by treatment and time. Results based on fire and forest growth simulations. Models were parameterized with plot-level tree lists and scaled to the fireshed using remote sensing. The simulated fire occurs immediately after Year 0 is measured. Results for the treated fireshed only.
Figure 21. Trends in measures of forest health by treatment scenario. For the fire scenarios, forest health is expressed as the fraction of the Year 0 basal area that is retained (red bars). For the no fire scenarios, forest health is expressed as the relative growth efficiency (blue bars). The simulated fire burns immediately after Year 0 is measured. Results for the treated fireshed only.
INTRODUCTION

Fire is a key ecological process in western forests that impacts nutrient cycling (Agee 1993), vegetative regeneration, species composition, stand structure (Stephens et al. 2009), air quality (Stephens et al. 2007), and ecosystem resilience (Holling and Meffe 1996). A century of fire suppression and logging practices of the early 20th century have greatly altered many American forests that once burned frequently, creating more dense (Covington and Moore 1994), homogenous forests that are less resilient to drought, insect attack and are more likely to burn at high severity (Miller et al. 2009, Mallek et al. 2013). Understanding how to manage these forests to retain their invaluable ecosystem services (Hassan et al. 2005) and maintain resilience to climate change (Bonan 2008) and uncharacteristically large and severe fire will be one of the most important challenge for the US Forest Service and other forest managers in the next century.

Though the future promises to be different from the past and historical conditions may not be appropriate targets for future management (Millar et al. 2007), understanding historical disturbance regimes, with which native plants and animals have evolved over thousands of years, is vital for those interested in building resilient ecosystems that can accommodate the uncertain future that lies ahead (Landres et al. 1999). There is growing evidence that the heterogeneity created by historical fires is vital for maintenance of species diversity and ecosystem resilience (North 2012). Understanding spatial and temporal components of these historical fire regimes
can help us incorporate natural or planned disturbance in management plans aimed to promote ecosystem resilience (Holling 1973).

Temporal components of historical fire regimes in the mixed conifer forests of the Sierra Nevada have been well studied (Kilgore and Taylor 1979, Swetnam 1993, Swetnam et al. 2000, Stephens and Collins 2004, Scholl and Taylor 2010), but there is still high uncertainty regarding spatial components of fire regimes in forests that historically experienced frequent, low to moderate severity fire (Taylor and Skinner 2003). There has been much greater success reconstructing spatial patterns in forests that historically experienced stand-replacing fires because ample evidence of these fires still exists. Estimations of spatial components of high severity, stand replacing fires, have been conducted using tree stand age, tree height, density and composition (Heinselman 1973, Hemstrom and Franklin 1982, Agee et al. 1990, Sibold et al. 2006) yet this evidence depends on high mortality rates, which rarely occupy more than small patches in areas that historically burned frequently (Collins and Stephens 2010). Additionally, much evidence of historic stand structure and disturbance regimes have been lost to fires or logging in forests that once burned frequently (Fulé et al. 1997), such as the mixed conifer forests of the Sierra Nevada.

The most reliable evidence left in frequent, low severity fire regimes is the presence of fire-scarred trees and a mosaic of multi-aged stands. Unfortunately, neither of these data sources lends clear evidence of the spatial patterns of fire. Since trees often survive low severity fires and recruitment is typically chronic, tree ages tell us little about the spatial patterns of frequent low severity fires. Fire scars are a unique source of data in which a positive scar is evidence of the presence of fire, but the “absence of evidence is not evidence of absence” (T.T. Veblen, personal communication, February, 2007). In other words, trees that experience fire often do not scar. In fact, Stephens et al. (2010) have shown that when the fire interval is less than 10 years, the probability of a previously scarred tree to scar again is only 5% in the mixed conifer forests of the Sierra Nevada and Baja California, Mexico. These ‘false negatives’ create spatially noisy datasets that make reconstructing spatial patterns of fire in these forest types difficult.

These problems have been partially overcome by using area-based rules to infer approximate fire sizes from the proportion of samples or geographic plots that record scars each year (Taylor and Skinner 1998) or by using expert opinion to construct fire polygons (Everett et al. 2000, Heyerdahl et al. 2001). These methods have been effective, but are difficult to
reproduce, and require some subjective decision-making. More recently, researchers have used automated methods in a GIS to produce objective fire areas across space and time. Hessl and others (2007) evaluated Thiessen polygons, kriging, and inverse distance weighted interpolation methods to reconstruct burned areas from binary fire scar data. Similarly, Collins and Stephens (2007) and Ferris and others (2010) used Thiessen polygons to reconstruct known fire areas from fire scar samples. Kernan and Hessl (2010) used an automated, spatially explicit inverse distance weighted interpolation method to create spatial mean fire interval maps of their study areas in eastern Washington, USA. This method has tremendous promise for understanding historical spatial fire dynamics via fire scar data, but the inverse distance weighting interpolation method can be problematic for data that contains many false negatives, such as fire scar data from frequently burned forests. As a result, the maps produced from this method can display inaccuracies around sample points due to the exact nature of the inverse distance weighting procedure.

In this manuscript, we reconstruct and compare both spatial and temporal fire regime metrics for two sites in the mixed conifer forest of the Sierra Nevada, California, USA. For each site, we explore the application of thin plate splines as a spatially explicit fire-mapping interpolation method with the ability to overcome problems introduced by false negatives that are often present in fire scar data from forests that once burned frequently. We also examine the potential bias in fire scar synchrony introduced by preferentially sampling trees with the most visible fire scars, as has often been done in fire history studies.

**Study sites**

Two mixed conifer forest watersheds were studied in the Tahoe and Sierra National Forests on the western slope of the Sierra Nevada Mountains of California (Figure 1). To evaluate and compare temporal and spatial components of their fire histories, we focused our sampling on the gridded network of forest inventory plots within treatment watersheds used in the Sierra Nevada Adaptive Management Project (http://snamp.cnr.berkeley.edu). For the northern study site, the Grouse Creek watershed (Last Chance) is approximately 2,358 ha, with elevation ranging from 800 in the southwest to almost 1,850 meters above sea level in the northeast portion of the study area. Sugar Pine is the treatment watershed for the southern study area (Sugar Pine), encompassing approximately 3,021 ha and elevation ranges from 1,200 m in the southwest to almost 2,200 m in the northeast portion of the study area at Speckerman
Mountain. The climate is of a Mediterranean type, characterized by warm, dry summers, and cool, wet winters. Annual mean precipitation, most of which falls as snow between November and April, is 118.2 cm at Last Chance (1990–2008; Hell Hole Remote Automated Weather Station) and 109.1 cm at Sugar Pine (1941-2002 in Yosemite National Park). Mean monthly temperatures are 3°C and 2°C in January and 21°C and 18°C in July for Last Chance and Sugar Pine, respectively. Soils are shallow (<1 m), well-drained, and developed in Mesozoic aged granite (Hill 1975). The terrain is moderately complex with a few areas of extreme slopes and major dissecting features such as large rivers or steep ridges.

Vegetation on these landscapes is typical of west-slope Sierra Nevada: a mixed conifer forest dominated by white fir (\textit{Abies concolor}), Douglas-fir (\textit{Pseudotsuga menziesii}), and incense-cedar (\textit{Calocedrus decurrens}) with sugar pine (\textit{Pinus lambertiana}), ponderosa pine (\textit{Pinus ponderosa}), and California black oak (\textit{Quercus kelloggii}) appearing as a codominant at variable densities throughout. Conifer forests at Sugar Pine differ from Last Chance in that there is no Douglas-fir in the Sugar Pine site. In addition to black oak, typical hardwood and shrub species include white alder (\textit{Alnus rhombifolia}), pacific dogwood (\textit{Cornus nuttallii}), whitethorn (\textit{Ceanothus cordulatus}), deerbrush (\textit{C. integerrimus}), and greenleaf manzanita (\textit{Arctostaphylos patula}). Forest structure varies by fire and timber management history, elevation, slope, aspect, and edaphic conditions (Scholl and Taylor 2010).

Fire history, inferred from fire scars recorded in tree rings, suggests a pre-Euro-American settlement fire regime with predominantly frequent, low-severity fires occurring at intervals ranging from 5 to 15 years (Stephens and Collins 2004, Scholl and Taylor 2010). Native American activity in the study area was likely high before European settlement, especially in the southern site. Up until 1901 the area that is now Bass Lake (approximately 9 km from the Sugar Pine study site) was a large, lush meadow which as a convergence spot for Sierra Miwok, Chuckchansi Yokut, and Western Mono tribes, who used fire extensively to keep the forest open, encourage herbaceous growth for game animals, and produce vegetative growth conducive to basket weaving and arrow construction (Anderson 2005, Penner Freedman 2013). This area was called Crane Valley by a detachment of the Mariposa Battalion in 1851, shortly after their “discovery” of Yosemite Valley (http://basslakeca.com/history.html). In 1901, Willow creek, which ran through Crane Valley, was dammed for the production of hydroelectric power, thus producing Bass Lake, which is still dammed today. From 1899 to 1931, the Sugar Pine Lumber
Company operated kilometers of narrow gauge railroad in and around the Sugar Pine study site. During that time, five wood burning locomotives hauled nearly 1.5 billion board feet (3.5 million cubic meters) of lumber from the forest (Johnston 1997). At the time there was not a market for incense-cedar wood, so the harvest was almost exclusively ponderosa and sugar pine.

The Nisenan Native American community once inhabited the forests of north-central Sierra Nevada (Matson 1972) in the area of the Last Chance site. Little detailed information exists about Native American activity in this area. Disease and activities associated with the discovery of gold in the mid-19th century devastated the population (Cook 1955, Wilson and Towne 1978). Mining operations had expanded rapidly producing $10 million of gold by 1868. As a result of tree harvesting and other land uses in the Sierra Nevada during the late 19th and early 20th centuries (McKelvey and Johnston 1992, Stephens and Collins 2004), current forest structure has comparatively higher surface fuel loads and tree densities, smaller average tree sizes, and a species composition that is dominated by shade tolerant species in most of both study areas (Parson and Debenedetti 1979, Stephens 2000, Scholl and Taylor 2010).

**Methods**

**Sample collection and processing**

In order to attain a geographically distributed collection of fire scars across the study areas, fire scars were sampled at grid points (n=75 for Sugar Pine and 71 for Last Chance) established at 500 m intervals, starting from a randomly chosen point (sensu Scholl and Taylor 2010). Each grid point was visited and 0-5 scars were sampled with a chainsaw within a 100 m radius of each point (approx. 3 ha search area). Emphasis was placed on objectively collecting as much fire-scarred material as possible in the search radius of each grid point. In addition to samples from the grid points, samples were collected when travelling from one grid point to the next, and were included in the present analysis at their sampled location (29 opportunistic samples at Sugar Pine (SP) and 27 at Last Chance (LC)). At the time of collection, sample tree species, diameter at breast/stump height, decay class (Waddell 2002), presence of bark, and geographic coordinates were recorded. A total of 148 samples were collected from live (n=61) and dead (n=87) fire scarred material at SP and a 134 samples were collected at LC (live n=42 and dead n=92).

Fire dates were determined by sanding each sample to a high polish and cross-dating each sample (Stokes and Smiley 1968, McBride 1983) against independent master tree ring
chronologies developed from increment cores from 30-50 trees without fires scars within the study area and/or nearby chronologies from Blodgett Research Forest (Stephens and Collins 2004) and the international tree ring database (www.ncdc.noaa.gov/paleo/treering.html). If possible, scar position within the annual ring was used to assign one of five seasonality categories to the fire event: 1) early earlywood (first third of the earlywood), 2) middle earlywood (second third of the earlywood), 3) late earlywood (last third of the earlywood), 4) latewood (within the latewood), or 5) dormant (on the ring boundary). Dormant scar position was interpreted as a fire after the growing season of the ring prior to the scar (late fall), rather than the early spring of the next growing season (prior to growth initiation of the next ring) (Caprio and Swetnam 1995, Scholl and Taylor 2010). Fire dates were checked by at least two researchers before being entered and summarized in FHX2 (Grissino-Mayer 2001). If samples contained too few rings to cross-date, were not able to be cross-dated, or were too decayed to sand or visualize, they were not included in the present analysis (n=30 at SP and 32 at LC). In total, 118 fire scars were successfully cross dated at SP and 102 at LC (Table 2-1).

**Non-spatial fire interval calculations**

In addition to temporal estimates of fire occurrence derived from the above spatially explicit method, point (PFI) and composite (CFI) fire return intervals were also calculated in FHX2 (Grissino-Mayer 2001). PFI are calculated from the intervals in each sample tree separately, and represent the mean fire return interval to a single point and are a more conservative estimate of fire frequency (Kitzberger and Veblen 1997). CFI are calculated using all the samples in the study and may be filtered by counting only years that scar a certain percent of the samples (typically 10-25%). CFI are more sensitive than point records to changes in burning conditions (Dieterich 1980), but are also highly scale and sample number dependent (increasing the scale or sample number typically decreases the CFI).

**Spatially Explicit Fire Area Reconstructions**

The time period from 1750 to 1900 was selected as a window in which to construct spatially explicit fire frequency maps for both study areas. This time frame was chosen because the fire scar sample depth drops considerably prior to 1750 and fire suppression practices were initiated shortly after the formation of the US Forest Service in 1905 (Scholl and Taylor 2010).
There have been reports of the fire intervals increasing in the second half of the 1800’s due to Euro-American settlement in the Cascade Range (Everett et al. 2000), Klamath Mountains (Fry and Stephens 2006), and North Coast Range (Skinner et al. 2009), but Scholl and Taylor (2010) did not detect a significant difference in fire interval statistics before 1850 (pre-settlement) and 1850 – 1904 (settlement) in a similar forest type in Yosemite National Park, nor do we detect a difference in fire frequency during the second half of the 1800’s. Thus, our window of time between 1750 and 1900 should adequately represent the fire regime in the study areas before modern day fire suppression.

Fire scar data from recording samples during this study period (116 out of 118 cross dated from SP, and 102 out of 102 cross dated from LC) was used to construct Spatial Mean Fire Interval (SMFI) maps for each study area. After a fire initially scars a tree, it is more sensitive to be scared by subsequent fires due to the wound left from the first scar (Kilgore and Taylor 1979). As a result, it is common to not consider a tree a potential fire “recorder” before it has been scarred for the first time. In the current study, two samples from Sugar Pine that had not scarred before 1900 were excluded from the analysis because they were not recorder samples during our study period. Of the samples at SP and LC, 61 (52%) and 42 (41%) were extracted from live trees respectively, and 57 (48%) and 60 (59%) were from dead snags, stumps, or remnant material (Table 1). Most of the samples at SP (86%) were from incense-cedar and the others (14%) were from ponderosa pine. In the LC site, 50% were from incense-cedar, 36% ponderosa pine, 12% sugar pine, and 1% Douglas fir (Table 2-1). Resulting fire scar density was 0.04 samples per hectare at both sites, which is comparable to sample densities in the fire history literature which range from 0.01 – 0.08 samples per hectare (Hessl et al. 2007).

For each fire scar sample, its fire years and geographic coordinates were input into a spatial points data frame in the R statistical package (R Development Core Team 2010). Individual samples were treated as binary point data across the study area. Fire perimeter maps were constructed for each year in which four or more samples recorded a fire to eliminate small spot fires or possible non-fire injuries (n=75 in Sugar Pine site and n=39 in Last Chance site), (Kernan and Hessl 2010). To do this, new spatial point data frames were constructed from only the recording samples for each fire year. Samples were coded as one (recording a fire) or zero (not recording a fire). For each year, the binary point data was then interpolated to construct a
grid with an estimated value between zero and one in every pixel. Two interpolation methods were used and will be compared in the following analysis:

1) Inverse Distance Weighting (IDW) – a deterministic, exact interpolation method that predicts a value for any unmeasured location by using the known values surrounding the prediction location. IDW is an exact interpolator, meaning the prediction surface passes exactly through the known sample locations, causing the maximum and minimum values of the interpolated surface to occur at sampled points. In this study, the resulting IDW surface ranged in value from a minimum of zero to a maximum of one, passing exactly through zero or one for each sample point. Measured values that are nearest to the prediction location will have greater influence on the predicted value at that unknown point than those that are farther away (Cressie 1993). Users can specify a power for IDW interpolation, which controls how quickly local influence diminishes with distance—lower power values give more influence to distant points and create smoother surfaces (Hessl et al. 2007). In addition to the power, users control the number of neighbors included in the local calculations. Hessl and others (2007) and Kernan and Hessl (2010) both use IDW interpolation to create SMFI maps using a power of two and 12 nearest neighbors. These same parameters were used in the current study and the gstat package (Pebesma 2004) for the R statistical package was employed for IDW interpolations.

2) Thin Plate Spline (TPS) – a deterministic, inexact interpolation method, which is a smoothed version of a spline (an exact interpolation method). We used the TPS algorithm from the Fields package in the R statistical package (Furrer et al. 2009). This algorithm fits a thin plate spline surface to irregularly spaced data with a smoothing parameter that is chosen by generalized cross-validation method, which minimizes the sum of squared errors of the fitted surface (Burrough and McDonnell 1998). The resulting surface does not necessarily pass through the values of the sample points (as it does with IDW interpolation) and generally gives a smoother fit (Craven and Wahba 1978) than exact interpolators which force the interpolated surface through the sample points.

Threshold values to differentiate burned from unburned pixels
In order to classify pixels as burned or unburned a threshold must be chosen as a cutoff. We implemented two threshold rules. First we used the proportion of scarred samples relative to the total number of recording samples, which has been used as a threshold for fire perimeter mapping (Hessl et al. 2007, Kernan and Hessl 2010) as well as predictive vegetation mapping (Franklin 1998).

As a more conservative threshold for fire area estimations, we also used half of the maximum value of the interpolated surface for the thin plate spline interpolation method. This midpoint of interpolation values represents an objective threshold that will predict more conservative fire sizes for our dataset than the proportion of recording samples scarred value because this proportion was always less than the midpoint in interpolation values.

Each interpolation method produced a surface of interpolated values for each fire year between 1750-1900 that scarred at least 4 samples (there were 75 years in SP and 39 years in LC in which 4 or more samples scarred). In each of these maps, the pixels greater than or equal to the threshold for that method were reclassified to a value of one and were inferred to burn in that fire year. Those below the threshold were reclassified to a value of zero and were inferred to have not burned. The fire size was calculated in each map for each fire year for each interpolation method. A map representing the number of times each pixel burned was then created from the sum of these resulting fire area maps for each interpolation method (hereafter called the ‘burn number’ map). Next, a map representing the number of fire intervals was made by subtracting one from each pixel on the burn number map (hereafter called the ‘interval number’ map).

Additionally, a ‘recording ring depth’ map was made for each interpolation method. To do this, the number of recording rings between 1750 and 1900 were calculated for each sample and the resulting values were interpolated with the same IDW and TPS methods described above (no cutoff value was necessary as pixels did not need to be classified as burned or unburned, and just retained the interpolated value indicating the number of recording years for that pixel). Finally, to compute a Spatial Mean Fire Interval (SMFI) map, we divided the recorder ring depth map by the interval number map (Kernan and Hessl 2010). For each SMFI map, the pixel values were averaged to estimate the SMFI for that site as a whole. These were computed for the three combinations of interpolation method and threshold values examined in this study:
1. Inverse distance weighting with a threshold of the proportion of recording samples that scarred
2. Thin plate spline with a threshold of the proportion of recording samples that scarred
3. Thin plate spline with a threshold of half the maximum interpolation value.

**Annual area burned and average fire size**

For each fire year (four or more samples recording fire), site, and interpolation method, we calculated the fire size by summing the area of all pixels classified as burned (regardless of their spatial continuity). These values were divided by the size of the study area to compute a proportion of the study area burned. For each site, these metrics were averaged across all analysis years to yield an average fire size and mean percent of the study area burned in a fire year.

**Natural fire rotation period**

Natural fire rotation periods (Heinselman 1973) were calculated for each study area and interpolation method by summing the total area burned during our 150 year analysis period and then using the following formula.

\[
\text{Fire Rotation Period} = \frac{\text{Total years in analysis period}}{\text{proportion of the study area that burned during this period}}
\]

**Spatial Mean Fire Interval map analysis**

To examine the relationship of slope aspect and SMFI, values from each of the SMFI maps were extracted to the sample grid points in each site in order to examine if significant differences existed in SMFI between slope aspect categories. Each point was classified with a predominant aspect of north (316° - 45°), east (46° - 135°), south (136° - 225°), or west (226° - 315°). Grid points in the various aspect categories were examined for variation in SMFI using a distribution-free Kruskal-Wallis \( H \) test (Scholl and Taylor 2010).

**Edge effects of interpolation methods:**
Undesirable edge effects can be introduced by spatial interpolation of point data and often vary by interpolation method, the relative location of sample points in reference to the edge of the interpolated surface, and the perimeter to area ratio of the interpolated surface (Helzer and Jelinski 1999). To investigate the impact of edge effects in each interpolation method compared in this study, we calculated the annual and average fire area, fire rotation period, and the spatial mean fire interval (SMFI) of various sized interpolation surfaces. We calculate these metrics for the full interpolation extent (defined by the maximum and minimum latitude and longitude of the full set of fire scar samples for each site) as well as extents that were cropped equally on all sides by 10 m increments until 50% of the study area was removed. The maximum crop distance that yielded reduction of the study area by 50% was 800 m for Sugar Pine and 670 m for Last Chance. Though the interpolation extent was iteratively cropped smaller and smaller, the point data for each fire year remained the same, effectively reducing the prediction at the “edge” of the data points with each iteration of a smaller extent (and leaving a number of the sample points outside the extent of the interpolation). The resulting curves for each fire metric were plotted as a function of proportion of the study area cropped from the perimeter, and each curve was fit to a linear regression model to examine if the slope was significantly different from zero, indicating a significant change in the metric with a change in the extent of the interpolation surface. Though it is expected that the fire metrics would change with different interpolation extents, our goal was to examine the resulting curves visually for any abrupt discontinuities that would indicate severe edge effects at the largest interpolation extent.

RESULTS

Non-spatial fire regime characterization

The point mean fire intervals (PFI) for Sugar Pine and Last Chance were 14.3 years and 17.5 years respectively, which represents the average time required for fire to re-scar the same sample within the study area (Table 2). The composite fire interval (CFI) for all fires (even those scarring fewer than 4 samples) was 1.1 and 1.2 years respectively, and increased to 5 and 6.1 years when only fires that scarred 10% of the recording trees were considered. In the SP site, there were not enough fire events that scarred 20% or 25% of the recording samples to calculate a statistic for the 20 or 25% composited fire interval. For LC, the composite 20% and 25%-scarred mean fire return interval was 11.0 and 19.8 years respectively (Table 2).
**Spatially explicit fire regime characterization**

Overall, in the analysis period from 1750 to 1900, there were 75 years in which four or more samples scarred in the Sugar Pine site and 39 years of four or more samples scarring at the Last Chance site. During those fire years there were a mean of 89.4 recorder samples at Sugar Pine and 80.1 at Last Chance (Table 3). On average seven samples (8%) were scarred during each fire year at Sugar Pine and 11.3 (14.5%) at Last Chance (Table 3).

Interpolation methods had similar trends in fire shapes for fire years, but varied in the resultant fire sizes and continuity (Figure 2). Both the interpolation method as well as the threshold chosen had a large influence on the resulting predicted fire area and shape. As an exact interpolation method, inverse distance weighting (IDW) forces the prediction surface to pass through the sample points, and as a result, the predicted fire perimeters often had unburned pockets around samples that did not record a fire that were close to samples that did (Figure 2). When the same threshold was used (the proportion of recorder samples that recorded a fire relative to all recording samples, hereafter called “proportion scarred”), IDW interpolation had a lower mean fire size (884 ha in Sugar Pine, 782 ha in Last Chance) than did the thin plate spline (TPS) interpolation method (1,105 ha in Sugar Pine, 980 ha in Last Chance, Table 4). When the same interpolation method (TPS) was used, but the threshold was changed from proportion scarred to half of the maximum value of the interpolated surface (hereafter called “half max.”), the resulting fire areas were smaller than both interpolation methods (TPS or IDW) when the proportion scarred threshold was used (565 ha in Sugar Pine, 514 ha in Last Chance, Table 4). Percent of the study area burned and fire rotation period (the time required to burn an area equal to the study area) are both a function of the area burned and followed similar trends (though a smaller average fire size yields a larger fire rotation period, Table 4).

The Spatial Mean Fire Interval (SMFI) maps from the various interpolations showed similar general trends in the sections of the study area that had the highest and lowest fire intervals, but varied in the predicted values (Figures 3 and 4). In Sugar Pine and Last Chance The IDW interpolation had an intermediate SMFI of 5.81 and 12.12 years respectively (mean of all pixels), and showed the greatest discontinuities in the predicted values for both sites. The resulting IDW SMFI map shows clearly the “bulls eye” pattern of higher fire intervals (lower fire frequency) around most of the sample points for both sites. The TPS interpolation with a
proportion scarred threshold showed the lowest SMFI of all the compared methods with an average of 3.12 years and 8 years for Sugar Pine and Last Chance respectively. Using the half max threshold, the TPS interpolation method resulted in the highest SMFI of 7.27 years and 21.79 years for SP and LC respectively (Figure 3, Table 4).

**Slope aspect and fire frequency**

No significant differences were detected in SMFI between plots in the four classes of slope aspect in any of the three interpolation methods (P > 0.05 for all tests: Kruskal-Wallis $H$ test) for either site. Figures 9 and 10 show the TPS half max. burn interval map with the topography of each study site.

**Seasonality**

Using the position of the fire scar within the annual growth ring, we were able to infer the seasonality of 85.8% of the fire scars dated in the Sugar Pine site and 94.2% in the Last Chance site (Table 1). In both sites, most of the fires occurred late in the growing season or after it had ended (latewood position = 45.9% of scars for Sugar Pine and 11.8% for Last Chance, dormant position = 49.3% of scars for Sugar Pine and 84.9% for Last Chance). Fires occurring during the growing season were less common with 3.3% of scars occurring in the late earlywood in Sugar Pine and 2.1% in Last Chance, and 1.5% of the scars occurring in the middle earlywood in Sugar Pine and 1.1% in Last Chance. None of the dated scars occurred in the early earlywood in Sugar Pine, and only one (0.2%) showed and early earlywood position in the Last Chance site (Table 1).

**Edge effects by interpolation method**

In general, no significant discontinuities in natural fire rotation or SMFI existed in the edge effect curves generated in our analysis (Figures 5-8) and consistent trends in edge effects for the compared interpolation methods were not obvious. For TPS half-max and IDW, there was a lack of consistent slope direction in edge effects for both natural fire rotation period and SMFI between the two sites. For TPS half max, the slope is significantly negative for fire rotation and SMFI in the Last Chance site, but in the Sugar Pine site, it is significantly positive for fire rotation and not significantly different from zero for SMFI. Similarly, For IDW, the
slope is significantly negative for fire rotation and SMFI in the Last Chance site, but in the Sugar Pine site, it is not significantly different from zero for either. The only consistent result for interpolation methods between sites in edge effects is for the TPS proportion scarred interpolation, that shows a significant negative slope on both natural fire rotation period as well as SMFI for both the Last Chance and Sugar Pine sites.

**Edge effects by site**

There were more robust patterns of edge effect at the site level (across all interpolation methods). Namely, for the Last Chance site, all interpolation methods showed significantly negative slopes for both natural fire rotation and SMFI (Figures 7 and 8). Whereas for the Sugar Pine site, only three of the six slopes (50%) were significantly different from zero (Figures 5 and 6). In this site, IDW had a non-significant slope for natural fire rotation period and both IDW and TPS half-max had non-significant slopes for SMFI.

**DISCUSSION**

**Latitude and fire frequency**

When only examining temporal dynamics, the two sites differed slightly in their fire regime statistics, showing less frequent fires and more synchrony in fire scar formation in the more northerly Last Chance site (Table 2). This is consistent with other studies in North America that have shown more frequent burning as latitude decreases (Heyerdahl et al. 2001). These differences become more pronounced when spatial dynamics are considered and modeled (Table 4). For instance, the 10% composite mean fire return interval for Last Chance (6.1 years) is 22% longer than that for Sugar Pine (5.0 years, Table 2), though when spatial dynamics are explicitly modeled using the TPS half-max method, the natural fire rotation period for Last Chance (9.3 years) is 69% greater than that for Sugar Pine (5.5 years). Similarly, the spatial mean fire return interval for Last Chance (8.0 years) was 156% larger than that for Sugar Pine (3.12 years). The increased difference in fire regime statistics when spatial dynamics of fire are explicitly modeled indicates that intervals alone relate only a fraction of the information available from fire scar samples. Without the explicit incorporation of geography, fire regimes characterization from fire scar samples results in homogenized statistics for the area of interest, which may mask important within-site heterogeneity in historical fire occurrence. Likewise, the
averaging of burn interval calculations to a heterogeneous study area, as has just been done with average SMFI values, relates only a fraction of the information that is produced with spatially explicit fire reconstruction. The resulting burn interval maps from the methods employed in this study characterize important spatial variation in historical fire occurrence (Figures 3 and 4) and will have tremendous benefits for better understanding and maintaining spatially variable disturbance patterns that facilitate spatial heterogeneity, which is increasingly becoming a management objective for maintenance of species diversity and ecosystem resilience (North 2012).

**High fire frequency and lack of fire scar synchrony in Sugar Pine site**

Curiously, in the Sugar Pine site, there were not enough years in which 20% of the samples scarred to calculate this composite statistic, which is not common for fire history studies in fire-frequent forests. One potential explanation of the lower level of synchrony of fire scars in this study include the occurrence of many small and patchy fires due to high Native American use and burning in this area (Anderson and Moratto 1996, Anderson 2005, Penner Freedman 2013). Crane valley, which is present day Bass Lake due to the damming of Willow Creek, which is in close proximity to the Sugar Pine study area was a vitally important confluence of at least three Native American Tribes, the Sierra Miwok, Chuckchansi Yokut, and Western Mono. These native people used this area extensively and used fire to manage the adjacent mixed conifer forest. This use would likely have been frequent enough to create very low intensity fires that did not scar most trees, but would have created a network of fire scared trees that in aggregation would create the quite low fire intervals elucidated in this study.

Another possibility is that the probability of scarring is different in incense-cedars and pines. Most other fire history studies use samples predominantly from pines (Stephens and Collins 2004), but because of the early 20th century logging of many pines in this area, most of the fire scar samples in the Sugar Pine site were from incense cedars (86%, Table 1). Cedars lack the flammable resin often found in and around pine fire scars, which could reduce the likelihood of cambial damage to an incense-cedar during a fire. Additionally, ponderosa pine litter depth is on average 5 times greater than incense-cedar litter depth (van Wagendonk et al. 1998), which could reduce the intensity and duration of surface fires under cedars and reduce
the likelihood of scarring, which across many samples would reduce the synchrony of scarring in cedars. This topic warrants further investigation.

**Comparison of interpolation methods**

As a result of the exact nature of IDW interpolations, the prediction surface must pass through the sample points. As a consequence, the resulting fire area maps for each fire year from the IDW interpolation method usually contained unburned pockets within burned areas surrounding recording samples that did not scar in that year (Figure 2). Similarly, the IDW fire number map and recording ring depth map both contained “bulls eye” discontinuities surrounding most of the sample points. An exact interpolation method will yield more accurate values at sample points, but given the nature of this dataset (with many “false negatives”), the IDW interpolation does not appear to be the best choice for reconstructing spatial fire dynamics due to the resulting discontinuities at sample locations (Figure 3). There is similar evidence of these artifacts around sample points in the IDW fire area maps published by Hessl and others (2007) and the IDW fire interval maps published by Kernan and Hessl (2010), but these maps do not show the extreme discontinuities that resulted in the current IDW fire interval map. This is likely due to the longer fire intervals in the higher latitude forests of Washington that were analyzed in these studies. With longer fire intervals, the scarring probability for recording trees is increased (Stephens et al. 2010), thus reducing the likelihood of false negatives which are the source of these discontinuities.

Thin plate splines are a good tool for smoothing noisy data (Craven and Wahba 1978), and effectively eliminated the interpolation artifacts around sample points for our dataset. However, accuracy at sample points is sacrificed for this smoothness. For datasets with many false negatives, such as the fire scar data presented in this study, a smoothing interpolation method likely gives a more realistic surface than exact interpolators such as IDW. With any interpolation method, the cutoff value for classifying pixels as burned or not has important consequences for the predicted fire sizes and fire regime descriptors (natural fire rotation and SMFI), as evidenced by the significant differences in the predictions of the thin plate spline interpolation method with a threshold of the proportion of the recording samples scarring versus half the maximum interpolated value (Table 4, Figures 3 and 4).
Without a known history of spatial fire dynamics in these areas during the study period, it is hard to quantitatively evaluate the accuracy of the results from this study. But we can compare the predicted fire sizes to other studies in nearby areas and with the well-accepted non-spatially explicit fire statistics calculated with the fire scar samples. In a recent study in a nearby forest in Yosemite National Park, Scholl and Taylor (2010) estimated the mean fire size for a comparable study period to be between 203-266 ha, but also made the qualification that many of these fires burned up to the edge of their study area, so were probably larger. In this study, the TPS interpolation method using a threshold of half of the maximum predicted pixel value predicted the smallest mean fire size and the closest to Scholl and Taylor’s estimate with a mean fire size of 565 ha (Table 4). The IDW method and the TPS method with a proportion scarred threshold predicted mean fire sizes of 884 and 1,210 ha, respectively in the Sugar Pine site.

Overall, the TPS with the half max threshold appears to be the most satisfactory method explored in the present analysis. The IDW interpolation method was inadequate because of the artifacts of lower fire frequency created around most of the sample points due to the presence of false negatives in our dataset. The TPS method with the proportion scarred threshold predicted fire sizes that were too large in relation to Scholl and Taylor’s (2010) estimates, and we believe consistently overestimates fire size.

Thin plate splines have promise for estimating spatial patterns of fire for areas that historically burned frequently and will likely have the presence of large numbers of false negatives in the fire scar record (Stephens et al. 2010). We prefer the objectivity of using a threshold of half the maximum interpolation value, but recognize that adjustment of this threshold may be necessary to fine-tune predictions of fire size for particular study sites.

We found, as did Kernan and Hessl (2007), that the SMFI was an intermediate value between the PFI, which is a conservative estimate of fire frequency, and the all sample CFI, which tends to estimate artificially low fire intervals (especially for large sample sizes). The SMFI of the TPS half max method (7.27 years for Sugar Pine and 21.79 for Last Chance) was only slightly higher than the 10% CFI (5.0 years for Sugar Pine and 6.1 years for Last Chance), which has often been used as an accurate statistic to describe fire frequency (Stephens and Collins 2004). Another advantage to the SMFI is that with adequate sampling density, it should be scale independent, which composited fire intervals are not (Kou and Baker 2006).
Aspect and fire frequency

While studies of mixed conifer forests in the Blue Mountains (Heyerdahl et al. 2001) and the Klamath Mountains (Taylor and Skinner 2003) have found evidence that northern facing slopes burn less frequently than south facing slopes, this study, nor one conducted in a site very near the Sugar Pine site (Scholl and Taylor 2010) did not find any differences in slope aspect and fire frequency. This is likely due to topography. Both studies that found differences in aspect were conducted in more complex terrain than those that did not find differences. When there are discreet features that separate slope aspects (such as steep ridges or large rivers) that can effectively limit the spread of fire, then differences in fire frequency are more likely between varying aspects or topographic facets. The current study sites did not have extreme terrain features that would be likely to limit fire spread. In the absence of features that effectively stop fire spread, it is not surprising that differences in fire frequency between slope aspects were not detected.

Edge effects

There was not significant evidence of extreme edge effects for any of the interpolation methods examined in this study. Instead, trends were idiosyncratic and seemed to depend heavily on the perimeter to area ratio of the study areas as well as the location of recording fire scar samples in each year during the study period (i.e. if there were no recording samples close to the edge of the interpolated surface for a particular year). For instance, the last chance site was a more elongated watershed and as a result has a 19% larger perimeter to area ratio than the Sugar Pine (7.31 x 10^{-4} versus 8.67 x 10^{-4} respectively, Figures 3 and 4). This likely influenced the finding that the slopes for all three compared interpolations had a significantly negative slope for both natural rotation period and SMFI (Figures 7 and 8) in the Last Chance site. Conversely, in the Sugar Pine site, only half of the interpolation slopes were significantly different from zero (Figures 5 and 6, IDW had a non-significant slope for natural fire rotation period and both IDW and TPS half-max had non-significant slopes for SMFI). The IDW interpolation method tended to extend the modeled fire perimeter into edge areas absent of recording samples (Figure 2), whereas the TPS interpolation did a better job of constraining the fire perimeter in the absence of recording scars along the edge (Figure 2). Edge effects were also likely buffered by the analysis period of 150 years, in which final burn interval maps and spatial fire regime statistics were the
combination of many fire years (75 fire years in the Sugar Pine site and 39 in Last Chance). Overall, edge effects did not seem to present major problems for any of the interpolation methods employed in this study, though this topic warrants further study, especially as it relates to the relative location of recording samples, the perimeter to area ratio of the study area, and the length of the analysis period and number of fire years.

Reconstruction of spatially explicit fire frequency maps holds great promise for informing landscape level disturbance-based adaptive management. Current forest management goals include the important idea that structural heterogeneity is key for ecosystem resilience and maintenance of species diversity (North 2012). Having a spatially explicit understanding of historical fire frequency will be valuable information as managers make pivotal decisions about how to intentionally create spatial heterogeneity that has been lost in many mixed conifer forests due to a century of homogenization from logging and fire suppression. The methods employed in this study can be applied to any fire scar collection that includes geographic locations for each sample. This could yield valuable spatially explicit information in areas where temporal dynamics have already been explored through the collection of fire scar data, or could be easily applied to new collections of fire scars to inform future resilience based ecosystem management.
References:


treatment effects on vegetation structure, fuels, and potential fire severity in western U.S. forests. Ecological Applications 19: 305-320.


Spatial and Temporal components of Historical Fire Regimes in a Mixed Conifer Forests, California

Kevin D. Krasnow, Danny L. Fry, and Scott L. Stephens

Table 1: Summary of fire scar samples and scar position from both study areas

<table>
<thead>
<tr>
<th></th>
<th>Sugar Pine</th>
<th>Last Chance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Size (ha)</td>
<td>3021</td>
<td>2358</td>
</tr>
<tr>
<td>Total samples cross dated</td>
<td>118</td>
<td>102</td>
</tr>
<tr>
<td>Live scars</td>
<td>61 (52%)</td>
<td>42 (41%)</td>
</tr>
<tr>
<td>Dead scars</td>
<td>57 (48%)</td>
<td>60 (59%)</td>
</tr>
<tr>
<td>Earliest dated fire scar</td>
<td>1607</td>
<td>1577</td>
</tr>
<tr>
<td>Most recent dated fire scar</td>
<td>1947</td>
<td>1943</td>
</tr>
<tr>
<td>Incense-cedar scars</td>
<td>101 (86%)</td>
<td>51 (50%)</td>
</tr>
<tr>
<td>Ponderosa pine scars</td>
<td>17 (14%)</td>
<td>37 (36%)</td>
</tr>
<tr>
<td>Sugar pine</td>
<td>0 (0%)</td>
<td>12 (12%)</td>
</tr>
<tr>
<td>Douglass fir</td>
<td>0 (0%)</td>
<td>1 (1%)</td>
</tr>
<tr>
<td>Total dated scars</td>
<td>802</td>
<td>659</td>
</tr>
<tr>
<td>Total scars with inferred seasonality</td>
<td>688 (85.8%)</td>
<td>621 (94.2%)</td>
</tr>
<tr>
<td>Early earlywood scars</td>
<td>0 (0%)</td>
<td>1 (0.2%)</td>
</tr>
<tr>
<td>Middle earlywood scars</td>
<td>10 (1.5%)</td>
<td>7 (1.1%)</td>
</tr>
<tr>
<td>Late earlywood scars</td>
<td>23 (3.3%)</td>
<td>13 (2.1%)</td>
</tr>
<tr>
<td>Latewood scars</td>
<td>316 (45.9%)</td>
<td>73 (11.8%)</td>
</tr>
<tr>
<td>Dormant position scars</td>
<td>339 (49.3%)</td>
<td>527 (84.9%)</td>
</tr>
</tbody>
</table>

Table 2: Point and composite fire-return interval statistics for the Sugar Pine (SP) and Last Chance (LC) study areas. “NA” indicates an insufficient number of samples to calculate a value.

<table>
<thead>
<tr>
<th>Site</th>
<th>Number of intervals</th>
<th>Mean FRI (yr)</th>
<th>Median FRI (yr)</th>
<th>SD (yr)</th>
<th>Min. (yr)</th>
<th>Max (yr)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SP</td>
<td>LC</td>
<td>SP</td>
<td>LC</td>
<td>SP</td>
<td>LC</td>
</tr>
<tr>
<td>Point (PFI)</td>
<td>500</td>
<td>475</td>
<td>14.3</td>
<td>17.5</td>
<td>11.0</td>
<td>15.0</td>
</tr>
<tr>
<td>Composite all</td>
<td>140</td>
<td>120</td>
<td>1.1</td>
<td>1.2</td>
<td>1.0</td>
<td>1.0</td>
</tr>
<tr>
<td>Composite 10%</td>
<td>27</td>
<td>24</td>
<td>5.0</td>
<td>6.1</td>
<td>3.0</td>
<td>4.5</td>
</tr>
<tr>
<td>Composite 20%</td>
<td>NA</td>
<td>9</td>
<td>NA</td>
<td>11.0</td>
<td>NA</td>
<td>9.0</td>
</tr>
<tr>
<td>Composite 25%</td>
<td>NA</td>
<td>5</td>
<td>NA</td>
<td>19.8</td>
<td>NA</td>
<td>15.0</td>
</tr>
</tbody>
</table>
Table 3: Fire scar sample summary during fire years analyzed in the 1750-1900 period (n = 75 years (Sugar Pine) and 39 years (Last Chance) when 4 or more samples scarred):

<table>
<thead>
<tr>
<th></th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean ± SD</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SP</td>
<td>LC</td>
<td>SP</td>
</tr>
<tr>
<td>Number recording</td>
<td>26</td>
<td>33</td>
<td>116</td>
</tr>
<tr>
<td>Number scarred in fire year</td>
<td>4</td>
<td>4</td>
<td>23</td>
</tr>
<tr>
<td>Percent scarred in fire year</td>
<td>3</td>
<td>4</td>
<td>25</td>
</tr>
</tbody>
</table>

Table 4: Comparison of mean fire size, percent of the study area predicted to burn, fire rotation period, and spatial mean fire interval (SMFI) for inverse distance weighting (IDW) and thin plate spline (TPS) interpolation methods with thresholds of the proportion of samples with a fire scar relative to the total number of recording samples in a particular year (Prop. scarred) and half of the maximum value in the interpolated grid for a particular year (Half max. value).

<table>
<thead>
<tr>
<th>Interp. method</th>
<th>Threshold for area burned</th>
<th>Mean area burned (ha) in years with 4 or more fires recorded</th>
<th>Mean percent of study area burned in years with 4 or more fires recorded</th>
<th>Fire rotation period (yr)</th>
<th>SMFI (yr)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>SP</td>
<td>LC</td>
<td>SP</td>
<td>LC</td>
</tr>
<tr>
<td>IDW</td>
<td>Prop. scarred</td>
<td>884</td>
<td>782</td>
<td>29 %</td>
<td>32 %</td>
</tr>
<tr>
<td>TPS</td>
<td>Prop. scarred</td>
<td>1,105</td>
<td>980</td>
<td>37 %</td>
<td>42 %</td>
</tr>
<tr>
<td>TPS</td>
<td>Half max. value</td>
<td>565</td>
<td>514</td>
<td>19 %</td>
<td>22 %</td>
</tr>
</tbody>
</table>
Spatial and Temporal components of Historical Fire Regimes in a Mixed Conifer Forests, California

Figure 1: Location of the northern (Last Chance) and southern (Sugar Pine) fire history study sites in the Sierra Nevada ecoregion (gray), California. Fire scars were sampled from trees within the forest inventory plot grid (circles) and opportunistically (stars).
Figure 2: Interpolated fire area (gray area) for 1844 and 1874 comparing Thin Plate Spline (TPS) with a threshold of the half the maximum value (top), TPS with the proportion of recording samples scarred threshold value (middle), and inverse distance weighting (IDW) with a proportion scarred threshold (bottom). Symbols are locations of recording trees scarred (x) and not scarred (circle) in the given year.
Figure 3: Comparison of fire-scar interpolated burn interval maps (top row) for Sugar Pine site, pixel value distribution for each map and mean pixel value (middle row), and annual area burned (bottom row) for IDW with a proportion scarred threshold (left column), Thin Plate Spline (TPS) with a proportion scarred threshold value (middle column), and TPS with a threshold of half the maximum cell value (right column).
Figure 4: Comparison of fire-scar interpolated burn interval maps (top row) for Sugar Pine site, pixel value distribution for each map and mean pixel value (middle row), and annual area burned (bottom row) for IDW with a proportion scarred threshold (left column), Thin Plate Spline (TPS) with a proportion scarred threshold value (middle column), and TPS with a threshold of half the maximum cell value (right column).
Figure 5: Assessing the edge effects of the three interpolation methods on SMFI in the Sugar Pine site. “β +” indicates a significantly positive slope when points are fit to a linear regression equation and “β −” indicates a significantly negative slope when points are fit to a linear regression equation. Absence of notation on a line indicates that the regression equation slope is not significantly different from zero.
Figure 6: Assessing the edge effects of the three interpolation methods on fire rotation period in the Sugar Pine site. “β +” indicates a significantly positive slope when points are fit to a linear regression equation and “β –“ indicates a significantly negative slope when points are fit to a linear regression equation. Absence of notation on a line indicates that the regression equation slope is not significantly different from zero.
Figure 7: Assessing the edge effects of the three interpolation methods on SMFI in the Last Chance site. “β +” indicates a significantly positive slope when points are fit to a linear regression equation and “β –” indicates a significantly negative slope when points are fit to a linear regression equation. Absence of notation on a line indicates that the regression equation slope is not significantly different from zero.
Figure 8: Assessing the edge effects of the three interpolation methods on fire rotation period in the Last Chance site. “$\beta+$” indicates a significantly positive slope when points are fit to a linear regression equation and “$\beta-$“ indicates a significantly negative slope when points are fit to a linear regression equation. Absence of notation on a line indicates that the regression equation slope is not significantly different from zero.
Figure 9: Spatial mean fire interval map for the TPS half maximum threshold interpolation method overlaid on topography for the Sugar Pine study site. Fire scar sample locations are shown with black dots.
Figure 10: Spatial mean fire interval map for the TPS half maximum threshold interpolation method overlaid on topography for the Last Chance study site. Fire scar sample locations are shown with black dots.