Forest Policy and Economics 87 (2018) 101–114

Contents lists available at ScienceDirect

Forest Policy and Economics

journal homepage: www.elsevier.com/locate/forpol

Changes in potential wildland fire suppression costs due to restoration treatments in Northern Arizona Ponderosa pine forests☆

Ryan A. Fitch[a,*], Yeon Su Kim[b], Amy E.M. Waltz[c], Joe E. Crouse[c]

[a] Alliance Bank Economic Policy Institute, Northern Arizona University, P.O. Box: 15066, Flagstaff, AZ 86011, United States
[b] School of Forestry, Northern Arizona University, 200 East Pine Knoll Drive, Flagstaff, AZ 86011, United States
[c] Ecological Restoration Institute, Northern Arizona University, P.O. Box 15017, Flagstaff, AZ 86011, United States

ARTICLE INFO

Keywords:
Wildfire suppression costs
Wildfire management policy
Burn severity
Forest restoration treatments
FlamMap
Northern Arizona

ABSTRACT

Wildfire suppression costs have been increasing since the early 1970's. With growing concern over wildfire suppression costs, our analysis addresses restoration treatment effectiveness in reducing wildfire suppression costs. We examine past fires across the Northern Arizona landscape to determine fire behavior characteristics that are significant in predicting wildfire suppression costs and capable of being modeled in fire simulations prior to wildfire events. We find burn severity metrics to be significant in predicting wildfire suppression costs. Three proposed treatment alternatives for the Four Forest Restoration Initiative (4-FRI) are analyzed to determine treatment effectiveness and policy implications in reducing burn severity metrics and wildfire suppression costs. The more aggressive treatments are more effective in reducing wildfire suppression costs except in the case of sever wind and weather events.

1. Introduction

Federal agencies, including the USDA Forest Service and Department of Interior (DOI), experienced a rising trend in wildland fire management expenditures beginning in 1971. A 2015 GAO report documented the average annual expenditure on wildland fire management activities at $3.4 billion over the 2004–2014 fiscal years (GAO, 2015). The appropriation for wildland fire management activities by the Forest Service and DOI more than doubled to an annual average of $2.9 billion during the 2001–2007-time frame compared to an annual average of $1.2 billion from 1996 to 2000 (GAO, 2009). This rising trend in wildland fire management expenditures is forecasted to continue in the future with higher frequency of wildland fire occurrences, longer durations of wildland fire seasons (Westerling et al., 2006), and the expansion of residential development within the wildland-urban interface (WUI) (Radeloff et al., 2005a, 2005b).

In previous studies wildfire size has been shown to be correlated with estimating suppression costs (Calkin et al., 2005; Liang et al., 2008; Thompson et al., 2013). If fire suppression costs are to be mitigated, it seems appropriate to focus on the factors, treatments, and policy that relate to fires categorized as "large" in size or where the severe wildfire threat is greatest (Pollet and Omi, 2002; Holmes et al., 2008). Our analysis expands on previous studies by examining burn characteristics of previous wildland fires that are significant in predicting wildfire suppression costs. Examining previous wildfires near our study area allows us to determine which fire behavior characteristics are useful in predicting suppression costs. We further seek wildfire behavior characteristics that can be modeled via fire modeling programs to determine wildfire suppression costs *ex ante*. Incorporating wildfire behavior results, we develop a regression model to predict wildland fire suppression costs. However, wildfire modeling is not without error. Incorrect use of model inputs and underprediction bias from the models impact the model outputs and the conclusions drawn from model outputs (Varner and Keyes, 2009; Cruz and Alexander, 2010). Our results are complementary to the future application of Risk and Cost Analysis Tools Package (R-CAT) (USDA Forest Service, 2010). R-CAT's general purpose is to standardize the methods for estimating risk reduction and cost savings resulting from land management proposals and treatments. R-CAT is required for all fire projects funded by the USDA Forest Service Collaborative Forest Landscape Restoration Program (CFLRP) and our results are not meant to replace the required procedure (USDA Forest Service, 2010).

2. Background

There have been considerable efforts to understand the factors affecting overall costs of wildland fires (e.g. Donovan and Rideout, 2003;

☆ This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.
* Corresponding author.
E-mail address: ryan.fitch@nau.edu (R.A. Fitch).

https://doi.org/10.1016/j.forpol.2017.11.006
Received 17 August 2016; Received in revised form 18 April 2017; Accepted 18 November 2017
Available online 06 December 2017
1389-9341/ © 2017 Elsevier B.V. All rights reserved.

Donovan et al., 2004; Gebert et al., 2007; Liang et al., 2008; Lynch, 2004; Prestemon et al., 2008; Donovan et al., 2011). Intuitively, one important factor is the increasing trend in total hectares (ha) burned by large wildland fires. Wildland fires < 122 hectares (ha) in size accounted for approximately 98.5% of the fires managed by the Forest Service from 1980 to 2002 but these small fires accounted for 6.2% of the total wildland fire suppression expenditures (Strategic Issues Panel on Fire Suppression Costs, 2004). A comparison of the average number of ha burned by wildland fires from 1970 to 1986 and 1987–2002 shows a stark increase from approximately 115,340 ha burned to over 405,000 ha burned annually (Calkin et al., 2005). For another comparison, 1700 fire ignitions burned about 1.21 million ha of forests in the Northern Rocky Mountains in 1910, while three ignitions triggered the Rodeo-Chediski and Hayman fires, which burned > 200,000 ha in 2002. While not studied directly, Calkin et al. (2005) reported that total hectares burned track wildland fire suppression costs "very well" on an annual basis. Large wildfires (> 400 ha) constitute a small number of total wildland fires that occur across the landscape (1.1%) and these large wildland fires accounts for 97.5% of the total hectares burned (Calkin et al., 2005). The frequency of large wildfires has markedly increased since the mid-1980s as there were almost four times as many large fires burning nearly seven times more land between 1987 and 2003 than compared to 1970 through 1986. The trend in the frequency of large wildfires has gotten worse and is projected to continue with warmer temperatures and earlier spring onset via climate change (Westerling et al., 2006). Although total fire size (area burned) increases overall suppression cost, expected suppression cost per ha decreases as fire size increases due to the fixed nature of many fire suppression related expenditures.

Total wildland fire suppression cost has been positively correlated with various spatial factors in addition to fire size. However, some of these factors have produced differing results. In a study that examined 100 wildland fires > 120 ha in size between 1996 and 2005, approximately 58% of the variation in wildland fire suppression costs was attributed to fire size and percentage of private land burned (Liang et al., 2008). After examining 1550 wildland fires across the US, Gebert et al. (2007) found that total housing value within 32 kilometers (km) of the wildland fire ignition point had a positive effect on expected suppression cost. Yoder and Gebert (2012) also found that housing values within a 20 mile radius of the wildfire contributes to an increase in estimated wildfire suppression costs. Complicating the hypothesis that the proximity of houses to wildfire increases suppression costs, Donovan et al. (2004) didn't find housing density or total housing to be significant in predicting wildfire suppression costs. Rather, fire size was again found to be the most significant variable (Donovan et al., 2004).

Increased wildland fire suppression expenditure has led to a growing interest in modeling effectiveness of fuel treatments; namely, changes in wildland fire burn probabilities and fire behavior due to fuel treatments (e.g. Ager et al., 2011; Calkin et al., 2005; Cochrane et al., 2012; Finney, 2005; Finney et al., 2005; Pollet and Omi, 2002; Stratton, 2004). The results of the fire modeling can be used to strategically locate fuel treatments in the landscape (Finney, 2005) and to estimate changes in expected suppression costs due to fuel treatments (Wildland Fire Management Risk and Cost Analysis Tools Package: R-CAT) (USDA Forest Service, 2010).

Fire modeling used to predict fire size, characteristics, and behaviors has limitations. Because wildland fire behavior is modeled over a given area of the landscape, the potential extent of a wildland fire cannot be modeled via fire behavior modeling programs (e.g. FlamMap) alone. ArcFuels, combined with fire behavior models was used to strategically implement optimal fuels treatments in Region 6 (Oregon and Washington, USA) by the US Forest Service (Vaillant et al., 2012). With the FlamMap fire model, pixels are assessed independently of each other regarding fire behavior.

Large wildland fires usually occur under the most extreme weather conditions (Finney, 2005). The creation of the landscape files that are used as inputs for modeling fire behavior are at the discretion of the modeler. These inputs determine fire behavior, thus consultation with an experienced fire ecologist should be considered to develop appropriate inputs for more accurate results. In addition, inputs such as fuel moistures; wind speed and direction; and weather conditions are needed in determining fire behavior. Varner and Keyes (2009) caution and elaborate on the need for accuracy clear statements of assumptions regarding parameter value inputs (e.g. fuel moisture and wind speed) (Varner and Keyes, 2009).

For modeling fire size, the FARSITE simulation system could be implemented which simulates wildland fire growth (Finney, 1998; Finney, 2004). FARSITE incorporates the above-mentioned inputs that FlamMap (Finney, 2006) uses but goes further to include a fire spread model, crown fire initiation model, crown fire spread model, and dead fuel moisture model.

Cruz and Alexander (2010) point out three main areas of bias that occur in fire modeling (Cruz and Alexander, 2010). Of first concern is the linkage of fire models that were created independently of one another but are used in conjunction with modeling fire behavior. Secondly, Rothermel's rate of fire spread models and Van Wagner's crown fire transition and propagation models have an underprediction bias in assessing modeled crown fire behavior. The final point of contention is the "crown fraction burned functions" (CFB functions) which are unsubstantiated by comparison to actual wildfire activity. We acknowledge the shortcomings and complexities of current fire behavior modeling tools and incorporate recommendations presented by Varner and Keyes (2009); Cruz and Alexander (2010).

There are social and political factors that affect fire managers' decisions and the expenditures committed for fire suppression efforts (Donovan et al., 2011). In addition to fire managers' decisions, land managers must also allocate resources to achieve goals of different treatments types (e.g. restoration treatments vs fuel load treatments) (Reinhardt et al., 2008; Stratton, 2004). Ecological restoration treatments can differ from fuel reduction treatments; they are not analogous. Ecological restoration is designed to return a current ecosystem to conditions representing a range of variation from multiple references. In the case of frequent-fire ecosystems like ponderosa pine (*Pinus ponderosa*) in the southwest USA, conditions from pre-fire exclusion (pre-European settlement) are used to describe a restored system (Covington and Moore, 1994). These restoration treatments include reintroducing pre-settlement fire regimes, species composition, species spatial patterns, and stand structures. Given today's overly dense ponderosa pine stands with larger fuel loads, ecological restoration treatments attempt to change fire behavior from high severity crown fires to low severity surface fires in modeling studies (Stephens, 1998; Stephens and Moghaddas, 2005; Fulé et al., 2001; Fulé et al., 2002; Roccaforte et al., 2009; Stephens et al., 2009). Ecological restoration in ponderosa pine meets Reinhardt et al.'s (2008) strict fuel treatment's objective as lessening fuel loads thereby reducing fire severity. Fuel treatments can achieve this objective. However, in those fire regimes where infrequent, stand-replacing fires are natural, fuel treatments could also create forest structures that are divergent from their historical structure.

Budgeting practices have been implemented as a method to help reduce expenditures on wildfire suppression costs. Efforts for better fire budgeting and planning started with the 1995 Federal Wildland Fire Policy and the National Fire Management Analysis System (NFMAS), a tool developed by the Forest Service (DOI Office of Policy Analysis, 2012). The efforts continue with the 2009 Federal Land Assistance, Management and Enhancement (FLAME) Act, which requires development of a National Cohesive Wildland Fire Management Strategy. The NFMAS seeks to optimize the Forest Service's fire budget for a given geographical area by minimizing wildland fire related costs, utilizing the known monetary costs associated with the "Cost plus Net Value Change" (C + NVC). However, after reviewing over 300 recommendations in the previous five years, the Strategic Issues Panel on Fire Suppression Costs (2004) characterized the federal agencies approach to fire suppression costs as “blank check management”. Since that time, several other spatial wildfire risk assessment tools have been developed (e.g. Rapid Assessment of Values At Risk (RAVAR) and the National Wildfire Hazard and Risk Assessment) (Calkin and Gebert, 2009). The key question remains unanswered: if and how fuel treatments or ecological restoration treatments reduce wildland fire suppression costs in any significant magnitude. The development of R-CAT is to directly address this question for collaborative forest landscape restoration programs. Namely, R-CAT provides a standardized tool for assessing wildfire risk reductions and cost savings for projects that might be funded through the USDA Forest Service CFLRP. CFLRP allocates Forest Service funds to projects that are competitively chosen with the goals of reducing fuel loads and implementing ecological restoration treatments and monitoring. Up to 50% of these costs can be covered by CFLRP funds.

The C + NVC model offers a theoretical framework to the relationship between wildland fire suppression costs and fuel treatments. The total of wildland fire costs is represented by C + NVC. In the general case of the C + NVC, costs, denoted by C (our cost measure of interest in this analysis), are all costs associated with wildland fire suppression and presuppression efforts, including fuel treatments; NVC represents all other fire related loss including property damage, fatalities and other value changes in marketable goods and non-market ecosystem services. Some aspects of fuel treatments can be considered as substitutes for suppression costs for a given level of NVC, while some components of fuel treatments can complement those in fire suppression (Donovan and Rideout, 2003; Rideout et al., 2008). Thus, an increase in fuel treatments does not necessarily imply a reduction in suppression costs unless the desired level of NVC is held fixed. Rather than viewing fuel treatments as a substitute for fire suppression, fuel treatments and fire suppression expenditures should be viewed as inputs to NVC. Fuel treatments and fire suppression expenditures have their individual marginal and joint effects to changes in NVC (Rideout et al., 2008). Therefore, if we analyze tradeoffs between treatments and suppression costs, the NVC must be held constant to directly compare the impacts of the two decision variable inputs on costs.

3. Methods

3.1. Modeling of fire behavior characteristics

Our initial study area for fire behavior modeling is a portion of the Coconino National Forest (southwestern U.S.A.), south/southeast of the city of Flagstaff, Arizona, designated as restoration unit 1 (RU1) (Appendix A). At the time of this analyses we utilized the Draft Environmental Impact Statement proposed by 4FRI. Three of the four treatment alternatives were selected for analysis. We summarize the three treatment alternatives as the no treatment option, the preferred treatment option, and the medium treatment option. The preferred treatment option is the most aggressive in terms of treatment thinning intensity. Under the preferred alternative, 175,640 ha would be mechanically treated across the entire 4FRI treatment area. In addition, 240,072 ha would undergo prescribed fire. The medium treatment option proposes mechanically treating 157,221 ha. Additionally, 72,356 ha would be treated using prescribed fire. In this study, we are defining prescribed fire as fire's incorporation into land management protocols (Ryan et al., 2013). The medium treatment alternative was designed to address concerns about prescribed fire emissions. Treatments alternatives were based on 4FRI's 2013 proposed environmental impact statement (EIS) and final treatment parameters are expected to change.

The current conditions of the entire 4FRI landscape were used as a starting point to create the landscape files (LCPs) for the fire modeling carried out in FlamMap version 3 (Mary Lata, 2013 personal communication). LCPs consist of a compilation of data layers that include fuel models, canopy cover, height to live crown (canopy base height), canopy bulk density, slope, aspect, and elevation. For the RU1 area, 31% of the landscape had sampled data with the remaining proportion extrapolated to create the LPC's. Fuel models and canopy characteristics were altered to better capture regionally specific fire behavior and effects based on the recent Schultz Fire. Fuel models represent the fuel bed inputs that include the load, bulk density, fuel particle size, heat content, and moisture of extinction (Scott and Burgan, 2005). The proposed treatments were then implemented at the stand level across the LCP file and the Forest Vegetation Simulator (FVS) (Dixon, 2002; Crookston and Dixon, 2005) was used to project forest structure changes for the three treatment scenarios.

The Schultz Fire burned over 6070 ha north/northeast of Flagstaff in 2010. We utilized the fuel moisture conditions from the Schulz Fire for the RU1 area during the three-month fire season of the analysis (Mary Lata, 2013 personal communication). The wind and weather conditions for the fire behavior simulations were obtained from the Mormon Lake, Arizona remote automated weather station (RAWS) located within the RU1 study area. Wind and weather conditioning files were created from the RAWS weather data from the years 2008–2012 for the months of May, June, and July which comprise the fire season of our analysis. RAWS wind data was used in modeling wildfire behavior characteristics as an input for average wind speed and direction (azimuth degrees, where 0° implies north to south and 90° implies east to west up to 360°). Fire behavior characteristics we modeled at average wind speed, average wind speed plus one standard deviation, and average wind speed plus two standard deviations.

FlamMap version 5.0.1.3 was used to simulate the fire behavior characteristics of flame length and crown fire activity (Finney, 2006). FlamMap is a PC-based fire mapping and analysis program that estimates potential fire behavior characteristics for given weather and fuel conditions (Finney, 2006; Stratton, 2006). Flame length outputs were transformed into hauling categories as summarized in Ager et al.'s (2011) flame length categorization. Flame length categorization provides a metric as to how effective initial wildland fire suppression activities might be. Ager et al. (2011) summarize hauling category flame lengths of 0–1.2 m as being able to be held by hand lines at the front or on the flanks; 1.2–2.4 m flames are too large for hand lines to attack head on but dozers and engines can be effective; 2.4–3.4 m flames present problems such as torching, crowning, and spotting and head on attacks of the fire are usually ineffective; and 3.4 + meter flames result in crowing and spotting problems and head on attack efforts are ineffective.

Crown fire activity outputs from FlamMap are expressed in crown activity potential. The outputs are classified by active crown fire, passive crown fire, surface fire, and unburned. Crown fire activity was used in conjunction with flame length to estimate areas of high burn severity. In response to Varner and Keyes' (2009) crown fire underprediction bias, we used flame length in conjunction with crown fire activity to create a more robust approach for estimating high burn severity. Flame lengths are derived from fire line intensity outputs (Stratton, 2006). Our assumption of high burn severity incorporates a fire line intensity model output and a crown fire model output for burn severity estimations. If a pixel is in the active crown fire category or had a flame length of > 3.4 m, that pixel was estimated as high burn severity. The Scott and Reinhardt (2001) Crown Fire Calculation Method was used to calculate flame length and crown fire activity outputs in FlamMap (Scott and Reinhardt, 2001).

FlamMap outputs were transferred into ArcGIS Desktop 10 Service Pack 5 for geospatial referencing and analysis. Specifically, ArcGIS was used to categorize flame lengths and crown fire activity into the metrics discussed above and crop the FlamMap outputs within the boundaries of the RU1 treatment area. The spatial analyst tool, “Raster Calculator,” was used to combine the fire behavior metrics of flame length and crown fire activity to estimate burn severity. The number of hectares in each of the combined fire behavior metrics within the treatment area was calculated. The analysis for categorizing burn severity was grouped as follows: High burn severity was assumed if any given pixel had a flame length > 3.4 m or had an active crown fire classification. Mixed burn severity was assumed if any given pixel had a flame length > 2.4 m or had a torching or active crown fire classification.

3.2. Regression analysis and suppression costs estimation

We conducted a regression analysis based on wildland fires that occurred on the four national forests regionally specific to the treatment area proposed by 4FRI (Apache-Sitgreaves, Coconino, Kaibab, and Tonto National Forests), with the addition of the Prescott National Forest, to estimate wildland fire suppression costs. The Prescott National Forest was included to increase sample size in an area with ponderosa pine as a landscape cover type. Burn severity maps were obtained from the Monitoring Trends in Burn Severity website (MTBS) (MTBS, 2013). Data on 67 fires > 324 ha in size on northern Arizona National Forests between 2001 and 2011 was collected for the regression analysis. Historical wildfire suppression cost data was provided by the USFS Rocky Mountain Research Station.

Variables of interest identified and collected to predict wildfire suppression cost include dominant vegetation cover type, distance of the fire perimeter to the WUI (meters), proportion of private land burned, and total wildfire size (ha) (Table 1). Distance to WUI was calculated using designated WUI areas as defined by each of the national forests within the sample. A natural log transformed linear regression equation for predicting total expenditure and cost per hectare of suppression was utilized for analysis (Liang et al., 2008).

4. Results

4.1. Fire behavior characteristics

A lower proportion of the landscape burned at high and mixed severities in July compared to May and June. May also had the highest proportion of the landscape with high and mixed burn severities due to dryer weather conditions and higher wind speeds. As expected, the proportion of the landscape that burns with high and mixed severities increased as wind speed increased across all months.

Comparing high burn severity proportions of the landscape across treatment types, there is a large decrease between no treatment and the preferred and medium treatment alternatives. The preferred treatment type is the most effective in terms of reducing the proportion of the landscape that burns at high severity. With no treatment, the simulated proportion of the landscape burning at a high severity under the three different wind speeds would range between 4.28% and 33.85% (May); 1.98% and 2.13% (June); and 0.9% and 1.76% (July). The preferred treatment alternative results in the largest reductions in the proportion of the landscape burning at high severity under the three different wind speeds with ranges between 0.72% and 4.01% (May); 0.33% and 0.43% (June); and 0.02% and 0.13% (July). The medium treatment with less prescribed fire also reduces proportions of the landscape burning at high severity compared with the no treatment alternative but is not as effective as the preferred treatment alternative. The medium treatment alternative has proportions of the landscape burning at high severity under the three different wind speeds ranging between 2.38% and 8.48% (May); 1.14% and 1.42% (June); and 0.73% and 0.88% (July). Thus, treatment effectiveness in reducing burn severity would be greater during the month of May. The proportion of the landscape burning at high severity during the month of May would be six to eight times smaller under the preferred treatment alternative than under the no treatment alternative. The preferred treatment alternative reduces high burn severity by 2250–18,889 ha. While the reductions in percentage of landscape burning at high severity for different treatment types over the month of July are not as large compared to the month of May, the scale at which the reductions took place was much higher. The preferred treatment alternative is 13.5–45 times lower than the no treatment alternative in percentage of the landscape burning at high severity, corresponding to 558–1037 ha. The medium treatment alternative, in each scenario, falls between the no treatment alternative and the preferred treatment alternative in the percentage of the landscape burning at high severity.

Proportions of the landscape expected to burn at a mixed severity exhibited more variability between treatment types. In general, simulated outcomes of the medium treatment alternative were similar to the no treatment alternative for the months of July and June. However, a larger proportion of the landscape is expected to burn at mixed severity under the no treatment alternative than the medium treatment alternative for the month of May. Again, the preferred treatment alternative was the most effective in reducing mixed burn severity across the landscape for the months of June and July. With wind conditions two standard deviations above the average for the month of May, the preferred treatment alternative would generate the highest proportion of the landscape burning at a mixed severity. The no treatment alternative exhibited simulated mixed burn severity ranges under the three different wind speeds between 13.43% and 68.19% (May); 2.3% and 2.68% (June); and 1.9% and 1.96% (July). Under the preferred treatment alternative, the simulated ranges of mixed burn severity under the three different wind speeds were between 2.09% and 72.95% (May); 0.59% and 0.7% (June); and 0.12% and 0.24% (July). The simulated proportions of landscape burning at mixed severity under the three different wind speeds for the medium treatment alternative range between 4.18% and 58.33% (May); 2.54% and 2.72% (June); and 1.83% and 1.97% (July). The correlation between implementing treatments and reductions in burn severity were not as distinct using the mixed burn severity metric. Under the medium treatment alternative, the simulated landscape showed increases in the percentage burning at mixed severity compared with the no treatment alternative during the month of June. Additionally, for the month of July, the medium treatment alternative has a higher proportion of the landscape burning at mixed severity on the upper range of the simulations compared with the no treatment alternative. Comparing simulations of the no treatment alternative and the preferred treatment alternative at high and mixed burn severities, we observe similar patterns of burn severity reductions over the months of June and July. However, for the month of

Table 1
Dependent and independent variables used in the regression analysis.

Variable	Description	Source
Cost	Forest Service and DOI suppression expenditure	US Forest Service
Size	Number of hectares burned	www.mtbs.gov
Distance to WUI	Shortest distance from WUI perimeter to fire perimeter	National Forest website and www.mtbs.gov
Burn severity	Proportion of fire that burned at high, medium, and low severity	www.mtbs.gov
Private land	Proportion of fire burned in private land	www.land.state.az.us
Dominant vegetation type	Vegetation type that had the highest percent cover within the fire perimeter	National Forest website
Forest	Dummy variable for the National Forest in which the fire occurred	National Forest website

Table 2
Estimated high and mixed burn severities in hectares and percentage of landscape burned for the no treatment alternative.

	Total hectares	Estimated high burn severity area (hectares)	Estimated proportion of high burn severity	Estimated mixed burn severity area (hectares)	Estimated proportions of mixed burn severity
May avg. high wind	63,298	2710	4.3%	8500	13.4%
May avg. high wind + 1 std.	63,298	12,352	19.5%	19,818	31.3%
May avg. high wind + 2 std.	63,298	21,427	33.9%	43,161	68.2%
June avg. high wind	63,298	1255	2.0%	1457	2.3%
June avg. high wind + 1 std.	63,298	1304	2.1%	1564	2.5%
June avg. high wind + 2 std.	63,298	1349	2.1%	1694	2.7%
July avg. high wind	63,298	569	0.9%	1201	1.9%
July avg. high wind + 1 std.	63,298	790	1.2%	1216	1.9%
July avg. high wind + 2 std.	63,298	1117	1.8%	1238	2.0%

Table 3
Estimated high and mixed burn severities in hectares and percentage of landscape burned for the preferred treatment alternative.

	Total hectares	Estimated high burn severity area (hectares)	Estimated proportion of high burn severity	Estimated mixed burn severity area (hectares)	Estimated proportion of mixed burn severity
May avg. high wind	63,298	459	0.7%	1326	2.1%
May avg. high wind + 1 std.	63,298	1211	1.9%	17,219	27.2%
May avg. high wind + 2 std.	63,298	2538	4.0%	46,175	72.9%
June avg. high wind	63,298	211	0.3%	375	0.6%
June avg. high wind + 1 std.	63,298	245	0.4%	413	0.7%
June avg. high wind + 2 std.	63,298	273	0.4%	443	0.7%
July avg. high wind	63,298	11	0.0%	75	0.1%
July avg. high wind + 1 std.	63,298	24	0.0%	94	0.1%
July avg. high wind + 2 std.	63,298	80	0.1%	152	0.2%

Table 4
Estimated high and mixed burn severities in hectares and percentage of landscape burned for the medium treatment alternative.

	Total hectares	Estimated high burn severity area (hectares)	Estimated proportion of high burn severity	Estimated mixed burn severity area (hectares)	Estimated proportion of mixed burn severity
May avg. high wind	63,298	1506	2.4%	2644	4.2%
May avg. high wind + 1 std.	63,298	2686	4.2%	10,625	16.8%
May avg. high wind + 2 std.	63,298	5366	8.5%	36,923	58.3%
June avg. high wind	63,298	723	1.1%	1608	2.5%
June avg. high wind + 1 std.	63,298	803	1.3%	1655	2.6%
June avg. high wind + 2 std.	63,298	900	1.4%	1722	2.7%
July avg. high wind	63,298	465	0.7%	1160	1.8%
July avg. high wind + 1 std.	63,298	516	0.8%	1178	1.9%
July avg. high wind + 2 std.	63,298	556	0.9%	1248	2.0%

May with wind speeds two standard deviations above the mean, the simulation for the preferred treatment alternative predicts 72.95% of the landscape burning at the mixed burn severity compared to 68.19% of the landscape burning at a mixed severity under the no treatment alternative. The more open conditions of the landscape resulting from the preferred treatment alternative are allowing wind conditions to impact flame lengths and crown fire activity more drastically compared with the no treatment alternative. Appendix B demonstrates the distributions of high burn severities across the RU1 treatment area. Tables 2–4 report the predicted number of ha and percentage of the RU1 treatment area that burned at high and mixed burn severities for each of the treatment types.

4.2. Regression analysis and suppression costs

The explanatory power of our model is comparable to and exceeds other regression equations predicting suppression costs (Donovan et al., 2004; Gebert et al., 2007; Liang et al., 2008; Yoder and Gebert, 2012). Our regression equations for total suppression costs using the high and mixed burn severity metrics have a R^2 of 0.62 and 0.61 respectively.

As expected, total area burned was significant in predicting wildland fire suppression costs. However, we also found that the proportion of the wildfire that burned at high and mixed severity was significant and the overall model explained more variation in predicting fire suppression costs than previous studies (Liang et al., 2008). From the regression equations based on wildfires specific to five National Forests in northern Arizona, the model including the "high burn severity" explanatory variable rather than the "mixed burn severity" explanatory variable showed slightly more predictive power between the two models (higher R^2 with equal number of predictive variables).

Our analysis reveals a 1% increase in distance from the WUI results in an approximate 0.16% decrease in wildfire suppression costs using the high burn severity explanatory variable. Using the mixed burn severity explanatory variable, a 1% increase in distance from the WUI results in an approximate 0.17% decrease in wildfire suppression costs. A 1% increase in the proportion of the wildfire burning at high severity would increase suppression costs by approximately 6.43%. Alternatively, a 1% increase in the proportion of the wildfire burning at mixed severity would increase suppression costs by approximately 4.91%. Examining wildfire size, a 1% increase in ha burned results in an approximate increase of 0.53% and 0.7% in total wildfire suppression costs for the high and mixed burn severity equations respectively. A 1% increase in wildfire ha burned results in an approximate decrease of 0.47% and 0.3% in per hectare wildfire suppression costs for high and mixed burn severity equations respectively. The RU1 treatment area falls within the Coconino National Forest so this brings about a decrease of approximately 78.27% and 67.96% for high and mixed burn severities respectively. The Coconino National Forest neighbors the city of Flagstaff, the largest city in northern Arizona. We hypothesize the Coconino National Forest's proximity to Flagstaff's infrastructure and human capital for fire suppression as drivers in reducing wildfire suppression costs. All our regression models had p-values < 0.0001. In addition, each independent variable was significant at the 95% confidence interval. Table 5 summarizes the regression equations predicting suppression costs.

Table 5
Regression Results for Wildfire Suppression Estimations. Standard errors are reported in parentheses.

	ln total cost with high burn severity	ln total cost with mixed burn severity	ln per hectare cost with high burn severity	ln per hectare cost with mixed burn severity
Constant	10.1208	8.44	10.1208	8.44
	(1.2969)	(1.3219)	(1.2969)	(1.3219)
ln fire size	0.5282[b]	0.697[b]	− 0.4718[b]	− 0.303[a]
	(0.1526)	(0.1441)	(0.1526)	(0.1441)
ln distance to WUI	− 0.1565[b]	− 0.1715[b]	− 0.1565[b]	− 0.1715[b]
	(0.0463)	(0.0458)	(0.0463)	(0.0458)
% of high burn severity	0.0624[b]		0.0624[b]	
	(0.0188)		(0.0188)	
% of mixed burn severity		0.0479[b]		0.0479[b]
		(0.0149)		(0.0149)
Coconino national forest	− 1.5265[b]	− 1.1382[a]	− 1.5265[b]	− 1.1382[a]
	(0.4899)	(0.5022)	(0.4899)	(0.5022)
R-squared	0.6173	0.6139	0.3525	0.3469
Number of observations	67			

[a] Indicates significance at the 95%.
[b] Indicates significance at the 99%.

Fire behavior is the only explanatory variable that we allowed to vary throughout the regression estimations. Ranges in predicted total and per ha costs are similar between high and mixed burn severity for the June and July months with a much higher range for the month of May. Because of the drier weather conditions and stronger winds, more of the landscape is predicted to burn at a mixed severity in the month of May resulting in larger cost predictions using the mixed burn severity regression equation. The highest estimated wildfire suppression costs occur when wind inputs were modeled at two standard deviations above their mean (24 km/h) during the month of May. In this analysis, the no treatment alternative has a total predicted suppression cost ranging between \$2.4 million and \$15.3 million with per ha estimates ranging between \$38 and \$242/ha if a wildfire burns the entire study area using the high burn severity metric. Under the medium burn severity metric, the total predicted suppression cost. The preferred treatment alternative results in approximately 73% of the landscape estimated to burn at mixed severity. From the regression sample, the highest proportion mixed severity fire was at approximately 68% of the landscape. Because the preferred treatment alternative exceeds the upper bound of the sample, we are not using this regression analysis to predict fire suppression costs outside the range of model calibration. The estimated suppression costs would range between \$3.1 million and exceeding \$19.4 million with cost per ha estimates ranging between \$20 and exceeding \$124/ha. The total predicted suppression costs of the medium treatment alternative range between \$3.9 million and \$14.2 million with per ha costs ranging between \$25 and \$91. Tables 6–8 summarize all estimated suppression costs under the varying wind conditions. However, if other factors of wildland fire costs, including rehabilitation and ecosystem service loss, are included in addition to suppression costs, the total cost of wildfires has been estimated to be in the range of 2 to 30 times greater than the costs associated with suppression alone (Western Forestry Leadership Coalition, 2010).

5. Discussion and conclusions

Much of the recent literature on forecasting suppression costs of large wildfires has indicated that the size of the wildfire is a significant explanatory variable (Calkin et al., 2005; Liang et al., 2008; Thompson et al., 2013). However, using wildfire behavior characteristics has not been examined. Our analysis expands the methodology of predicting wildfire suppression costs by incorporating a statistically significant, burn severity variable into a semi-log transformed regression equation. Fire behavior characteristics (e.g. burn severity) can be estimated through various wildfire models. Our analysis links the outputs of wildfire models into methodology land managers can use to assess the effects of fuels and restoration treatments on wildfire suppression costs. However, using wildfire models to predict changes in wildfire behavior should be approached with caution (Varner and Keyes, 2009; Cruz and Alexander, 2010).

Comparing actual wildfire behavior to modeled wildfire behavior shows an underprediction bias in the models (Cruz and Alexander, 2010). Wind and weather conditions have a major impact on fire model outputs and errors can occur with incorrect inputs (Varner and Keyes, 2009). FlamMap holds wind and weather conditions constant across the landscape (Stratton, 2006). Wildfires never operate under the constant inputs used in the fire models thereby influencing model outputs. In addition, our study assumes that burn severity can be derived from the FlamMap fire model outputs of "crown fire activity" and "flame length". Understanding the limitations of the fire models and limiting model bias from wind and weather inputs is a necessity. We used onsite wind and weather data to address potential model bias from decision variable inputs. Our assumption for measuring burn severity was implemented to address the underprediction bias of wildfire models (Cruz and Alexander, 2010). Until more dynamic fire modeling programs are developed, the assumptions and constraints of current fire models must

Table 6
The no treatment alternative's total cost and per hectare cost estimations under the different wind and weather conditions for the fire season months of May, June and July.

	Total cost under high burn severity	Total cost under mixed burn severity	Per hectare cost under high burn severity	Per hectare cost under mixed burn severity
May avg. high wind	$2,424,239	$6,266,865	$38	$99
May avg. high wind + 1 std.	$6,271,644	$14,757,512	$99	$233
May avg. high wind + 2 std.	$15,343,070	$86,332,461	$242	$1364
June avg. high wind	$2,100,303	$3,677,767	$33	$58
June avg. high wind + 1 std.	$2,110,473	$3,707,667	$33	$59
June avg. high wind + 2 std.	$2,119,856	$3,744,321	$33	$59
July avg. high wind	$1,962,963	$3,607,205	$31	$57
July avg. high wind + 1 std.	$2,006,198	$3,611,302	$32	$57
July avg. high wind + 2 std.	$2,071,924	$3,617,319	$33	$57

be understood to interpret the outputs. Our analysis acknowledges these constraints but shows how fire modeling techniques can be implemented into the wildfire suppression cost estimation process.

The results of this study identify several management implications and important research areas for the future. Our wildfire simulations show high severity burn conditions are interspersed throughout the landscape under the current conditions while the post-treatment configurations change to a disconnected, spotty, configuration (Appendix B). This may affect the wildfire suppression cost estimates as areas under “severe” conditions could be allowed to burn until the wildfire reaches areas with decreased severity measures where suppression efforts are more effective. For example, hand crews are not able to deal with excessively high flame lengths and crown fire activity (Vaillant et al., 2012). Focusing hand crew suppression efforts on areas that exhibit lower predicted severity (smaller flame length or surface fires) would be more effective. Fuel treatments may create unintended negative externalities as they reduce burn severity of the treated area but may increase severity in adjacent, non-treated areas. Values at risk in the adjacent areas should be examined before treatment implementation with respect to wind direction and fire spread probabilities (Calkin et al., 2014).

Results have differed in quantifying the effects that proximity of values at risk (e.g. homes) have on wildfire suppression costs. This study and others (Gebert et al., 2007; Liang et al., 2008; and Yoder and Gebert, 2012) found the wildfire's proximity to homes or WUI areas to be significant in predicting suppression costs. However, Donovan et al. (2004) found no such relationship significant. Other non-spatial factors that have been used in predicting wildfire suppression costs include media coverage and political influence (Donovan et al., 2011). Given the large number of factors that have been shown to influence wildfire suppression costs, further investigation into non-spatial factors of wildfire costs (e.g. length of time the wildfire burns and types of resources deployed, and number of fire crews used) could increase model precision.

Our analysis holds the net value change of ecosystem goods and services constant across the landscape to allow for the analysis of tradeoffs between suppression costs and treatments (Rideout et al., 2008). However, an ecosystem's ability to deal with disturbances (e.g. fire) influences the net value change. A low severity fire in a fire adapted ecosystem is not expected to cause a shift in the ecosystem type or the services the ecosystem carries out; a low severity surface might even be beneficial to the ecosystem and increase or provide beneficial inputs for NVC (Hurteau and North, 2009). High burn severity fires have the ability to change the southwest ponderosa pine ecosystem and its functions (Savage and Mast, 2005). Whether society gains or losses from an ecosystem change is beyond the scope of this paper but worth further investigation to determine society's preferences and values of ecosystem types.

Table 7
The preferred treatment alternative's total cost and per hectare cost estimations under the different wind and weather conditions for the fire season months of May, June and July.

	Total cost under high burn severity	Total cost under mixed burn severity	Per hectare cost under high burn severity	Per hectare cost under mixed burn severity
May avg. high wind	$1,941,791	$3,641,488	$31	$58
May avg. high wind + 1 std.	$2,091,213	$12,122,655	$33	$192
May avg. high wind + 2 std.	$2,383,480	N\A	$38	N\A
June avg. high wind	$1,894,894	$3,388,633	$30	$54
June avg. high wind + 1 std.	$1,901,256	$3,398,391	$30	$54
June avg. high wind + 2 std.	$1,906,511	$3,406,115	$30	$54
July avg. high wind	$1,857,899	$3,312,570	$29	$52
July avg. high wind + 1 std.	$1,860,282	$3,317,337	$29	$52
July avg. high wind + 2 std.	$1,870,580	$3,331,929	$30	$53

Table 8
The medium treatment alternative's total cost and per hectare cost estimations under the different wind and weather conditions for the fire season months of May, June and July.

	Total cost under high burn severity	Total cost under mixed burn severity	Per hectare cost under high burn severity	Per hectare cost under mixed burn severity
May avg. high wind	$2,155,714	$4,027,835	$34	$64
May avg. high wind + 1 std.	$2,411,966	$7,365,220	$38	$116
May avg. high wind + 2 std.	$3,154,286	$53,764,797	$50	$849
June avg. high wind	$1,987,748	$3,712,847	$31	$59
June avg. high wind + 1 std.	$2,012710	$3,730,674	$32	$59
June avg. high wind + 2 std.	$2,025,309	$3,748,587	$32	$59
July avg. high wind	$1,938,747	$3,590,419	$31	$57
July avg. high wind + 1 std.	$1,950,883	$3,607,658	$31	$57
July avg. high wind + 2 std.	$1,963,095	$3,624,981	$31	$57

Low intensity fire regimes, corresponding to smaller flame length fires (0–1.2 m) with crown fire being a low probability event are the desired fire type for southwest ponderosa pine ecosystems (Covington and Moore, 1994; Swetnam, 1990). Restoration treatments in the southwest ponderosa pine ecosystem seek to reintroduce low intensity fire as an objective. There are costs associated with these types of fires, but we would expect the suppression costs to be lower as fire behavior is changed from high and mixed severity to a low severity. Instances with a naturally occurring wildfire under low burn severity conditions could be used as a management tool and ecological benefits of fire could outweigh the associated costs in suppressing these wildfire types (Ryan et al., 2013). This analysis shows that changing wildfire behavior correlates to changes wildfire suppression costs.

As with any restoration treatment, reducing the number of severe wildland fires is only one of the benefits. Other benefits include enhancement of additional ecosystem services like carbon storage, water yields and filtration, wildlife habitat, aesthetic quality enhancement, and recreational opportunities (Chazdon, 2008). Non-market benefits and costs should be included in the overall benefit-cost analysis of implementing restoration treatments. Further analysis of the NVC of the landscape following treatments and the effects of fire on the landscape needs to be carried out to determine a more holistic view of landscape value change. Our analysis shows the estimation of wildfire suppression costs is correlated with wildfire burn characteristics. Through wildfire modeling techniques, land managers can compare the effectiveness of restoration and fuel treatment projects in the context of wildfire suppression expenditure changes.

Acknowledgements

The authors would like to thank Mary Lata and Neil McCuster for assistance in fire modeling landscape files; Wally Covington, Diane Vosick, and the Ecological Restoration Institute for research assistance; and Julie Mueller for editing support.

Appendix A. Appendix A (Study Area)

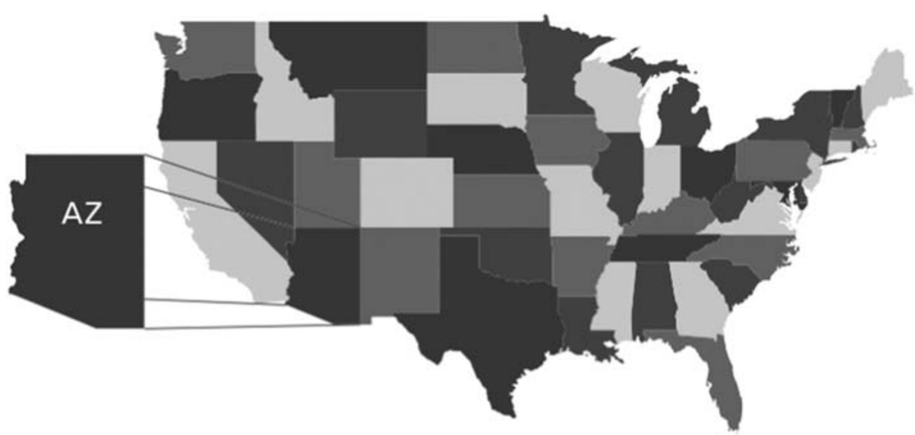

Fig. A1. Location of Arizona within the contiguous 48 states.

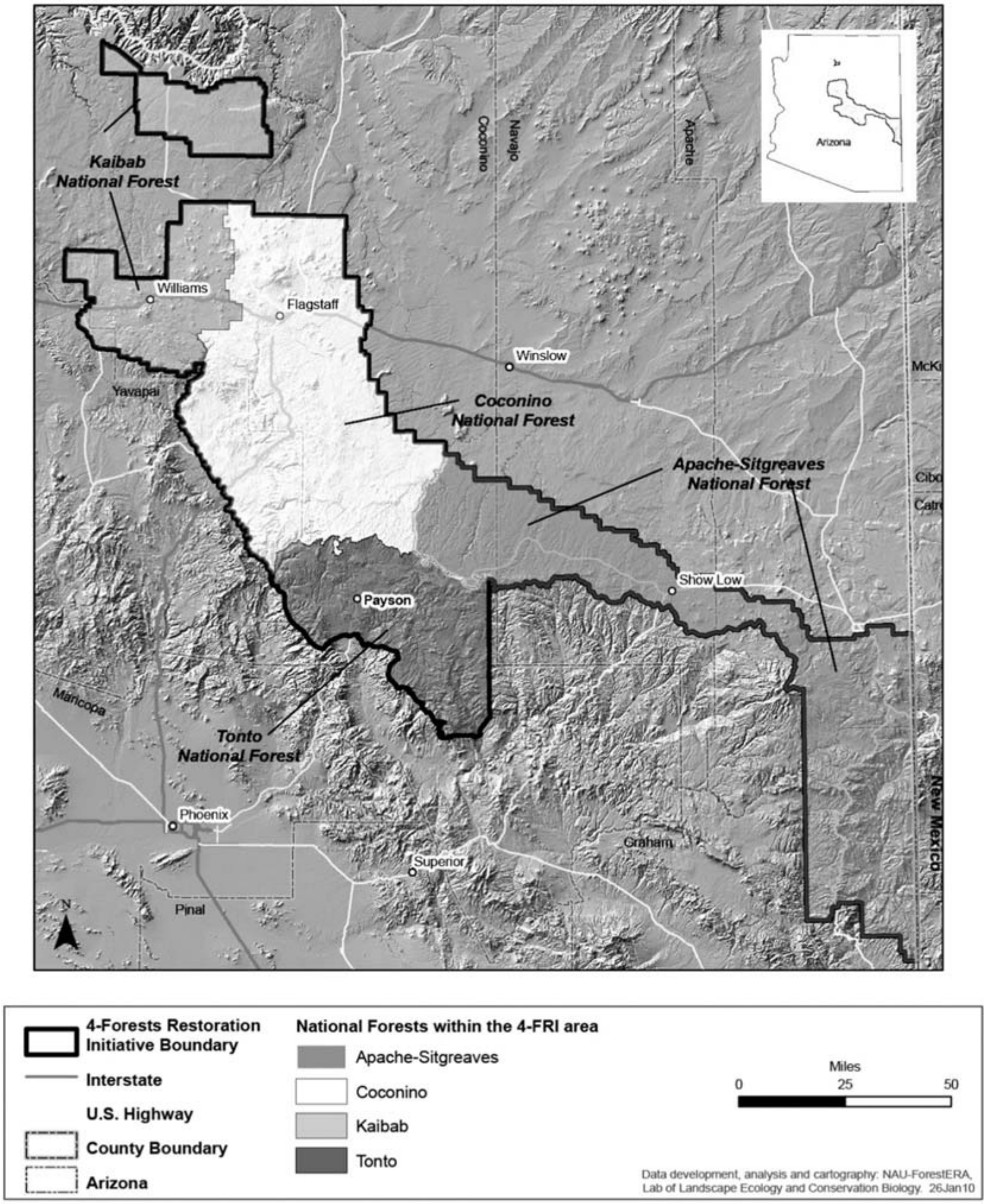

Fig. A2. Overview of the Four Forest Restoration Initiative's boundaries within four of the National Forests in northern Arizona.

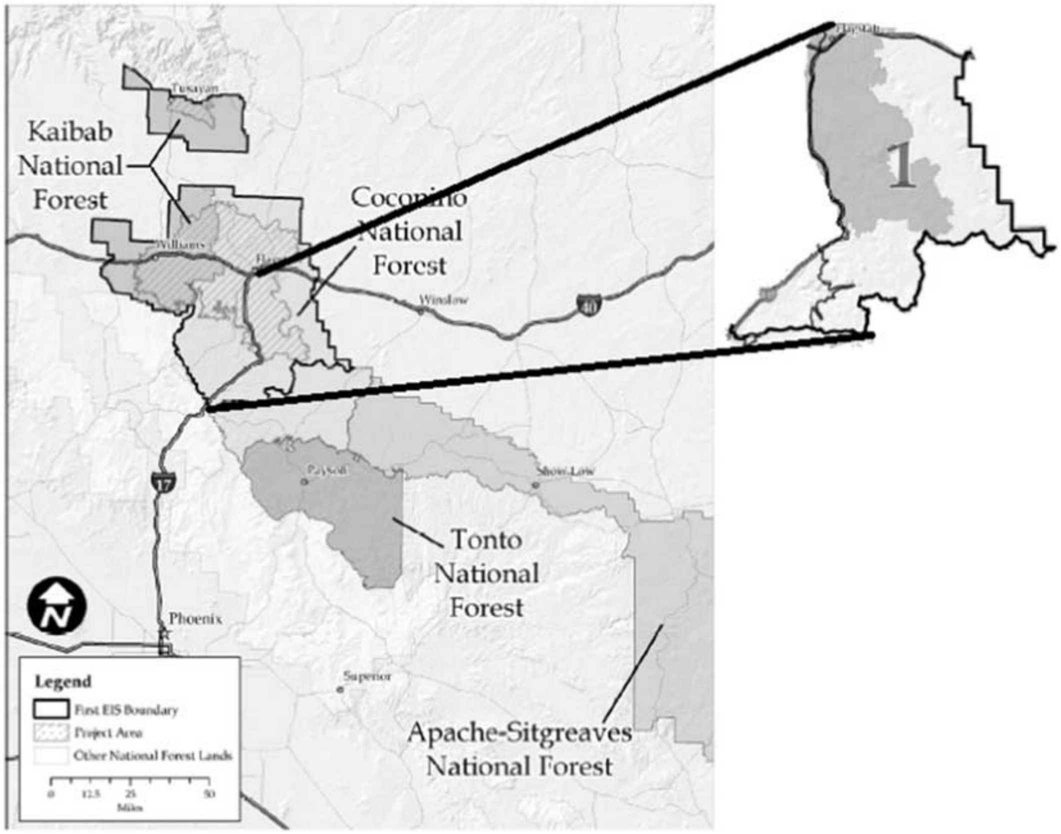

Fig. A3. Study Area of Restoration Unit 1 within the Coconino National Forest of the Four Forest Restoration Initiative's treatment area in northern Arizona.

Appendix B. Appendix B (High Burn Severity)

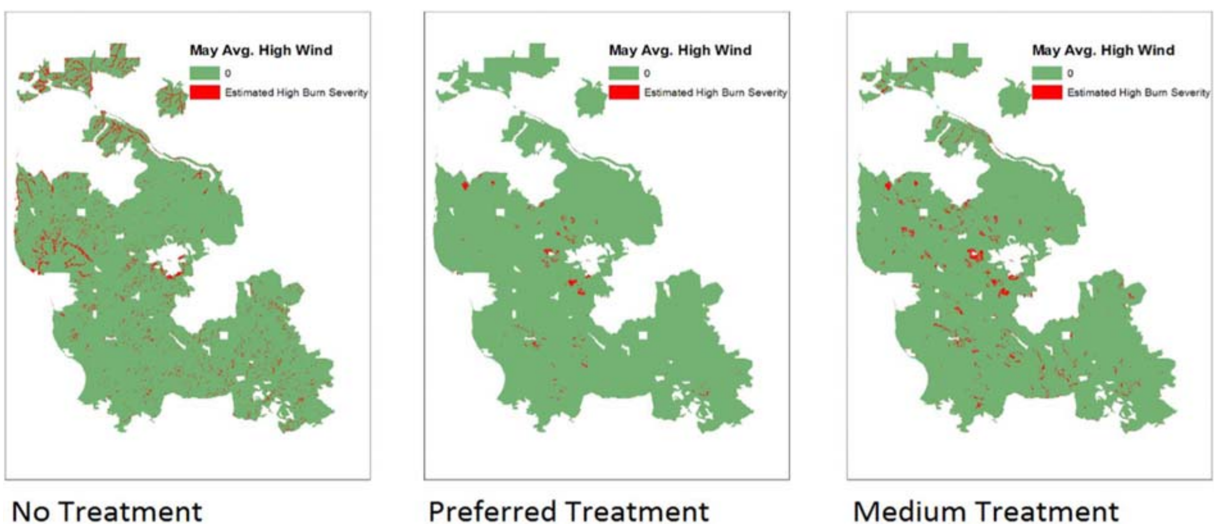

Fig. B1. Estimated high burn severity area (active crown fire or flame length > 3.4 m) of Restoration Unit 1 for May average wind conditions (24.8 kph at 160° azimuth) under the three treatment alternatives.

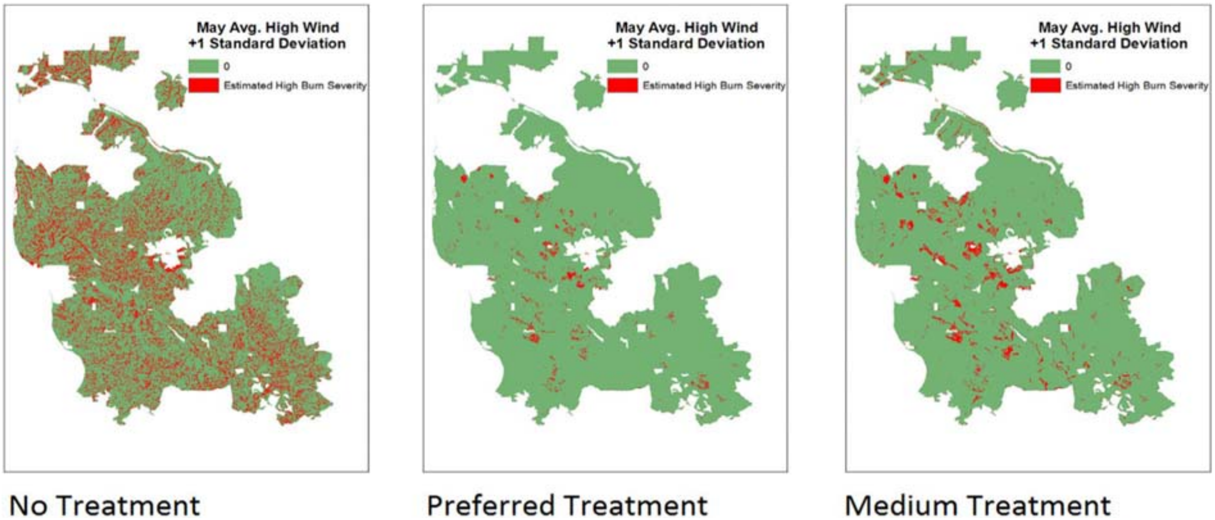

Fig. B2. Estimated high burn severity area (active crown fire or flame length > 3.4 m) of Restoration Unit 1 for May average wind conditions plus one standard deviation (31.2 kph at 160° azimuth) under the three treatment alternatives.

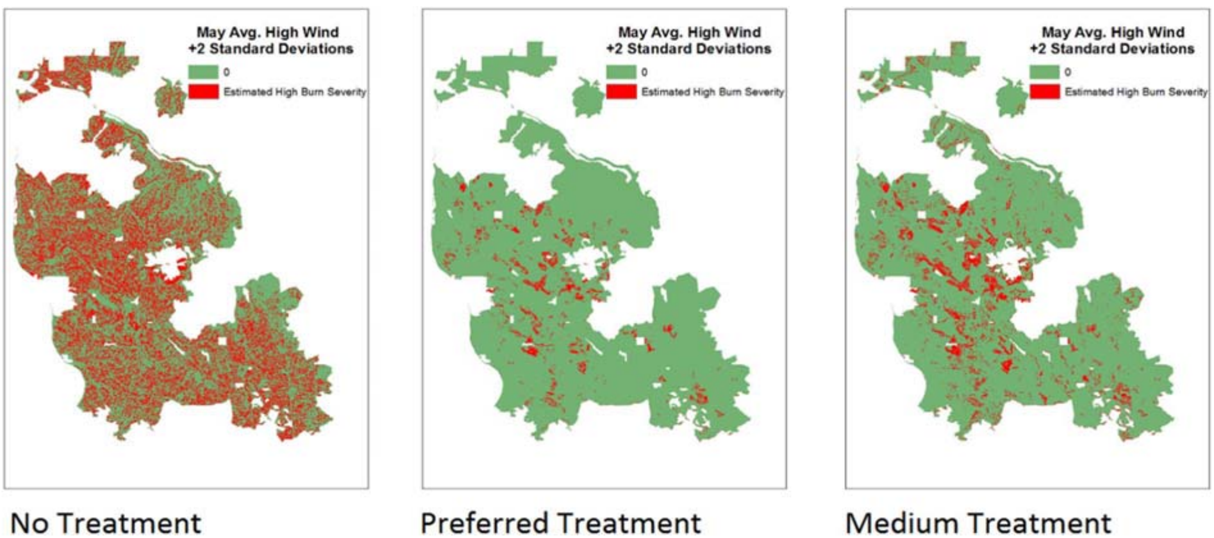

Fig. B3. Estimated high burn severity area (active crown fire or flame length > 3.4 m) of Restoration Unit 1 for May average wind conditions plus two standard deviations (37.7 kph at 160° azimuth) under the three treatment alternatives.

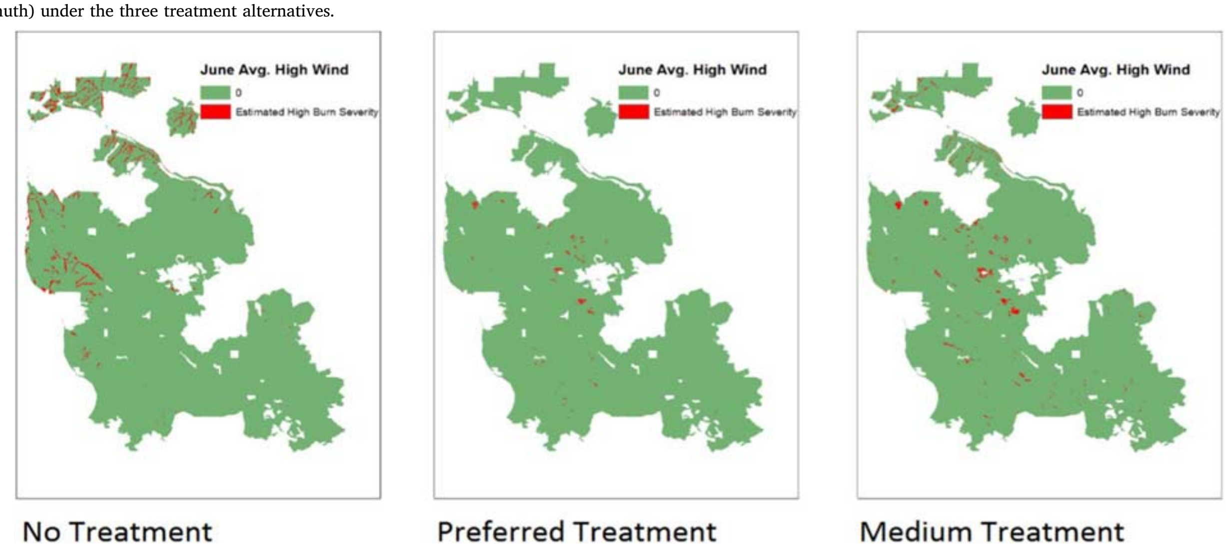

Fig. B4. Estimated high burn severity area (active crown fire or flame length > 3.4 m) of Restoration Unit 1 for June average wind conditions (21.2 kph at 173° azimuth) under the three treatment alternatives.

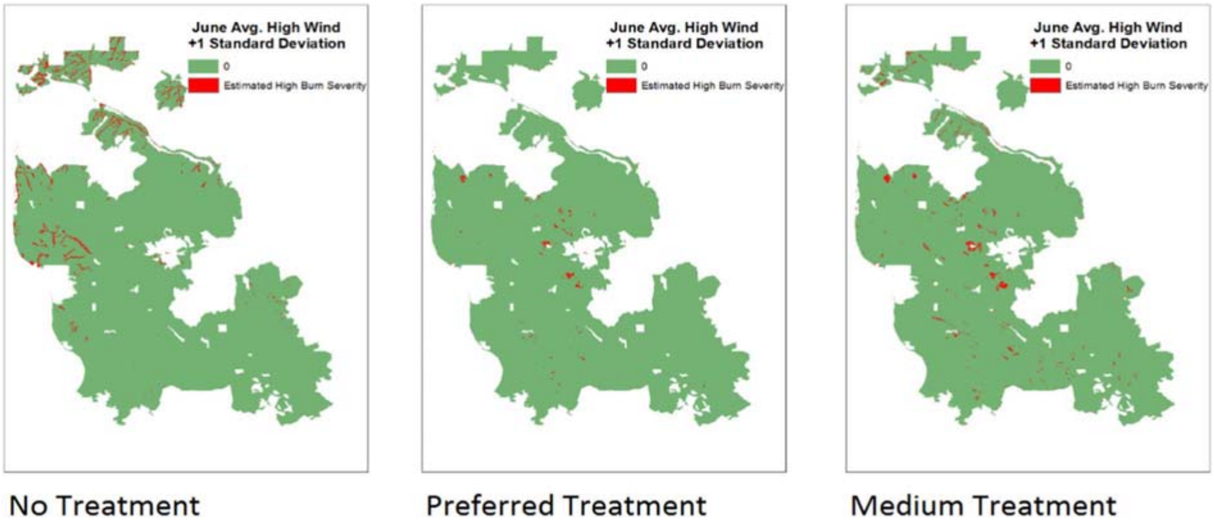

Fig. B5. Estimated high burn severity area (active crown fire or flame length > 3.4 m) of Restoration Unit 1 for June average wind conditions plus one standard deviation (22.5 kph at 173° azimuth) under the three treatment alternatives.

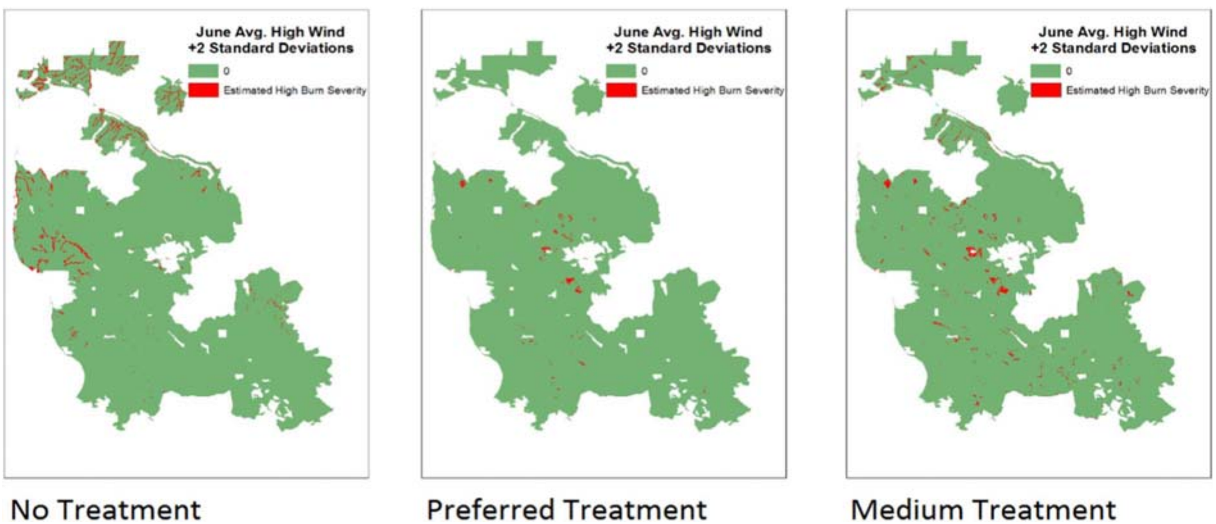

Fig. B6. Estimated high burn severity area (active crown fire or flame length > 3.4 m) of Restoration Unit 1 for June average wind conditions plus two standard deviations (23.8 kph at 173° azimuth) under the three treatment alternatives.

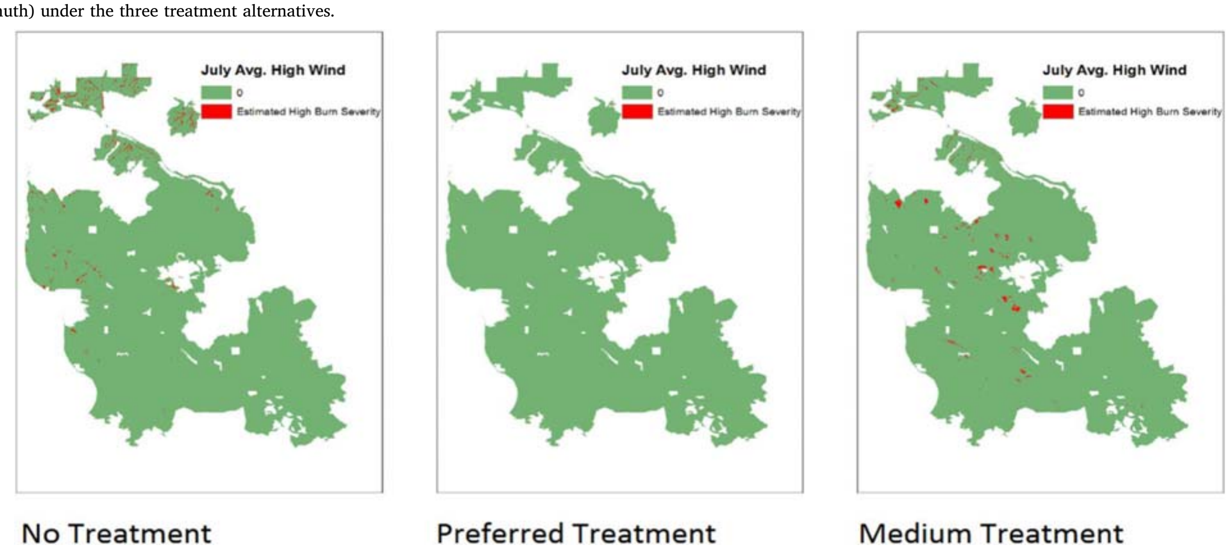

Fig. B7. Estimated high burn severity area (active crown fire or flame length > 3.4 m) of Restoration Unit 1 for July average wind conditions (17.7 kph at 178° azimuth) under the three treatment alternatives.

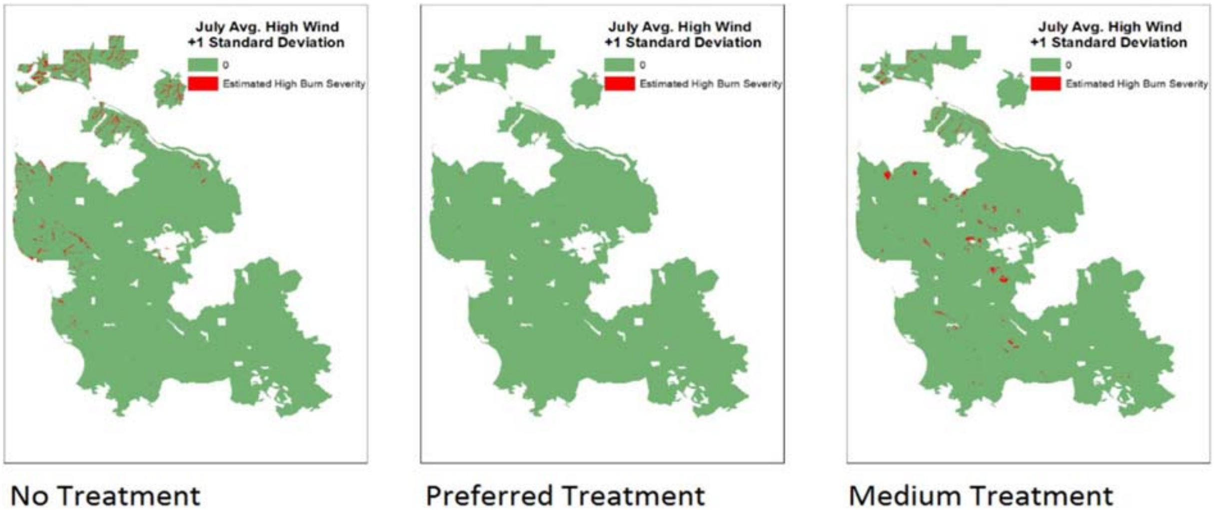

Fig. B8. Estimated high burn severity area (active crown fire or flame length > 3.4 m) of Restoration Unit 1 for July average wind conditions plus one standard deviation (19.6 kph at 178° azimuth) under the three treatment alternatives.

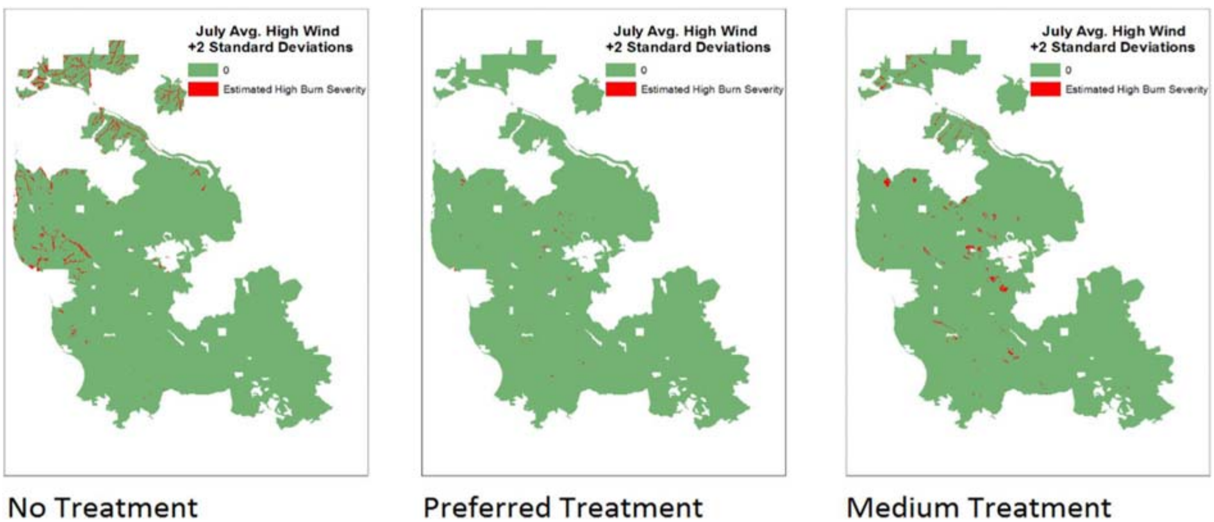

Fig. B9. Estimated high burn severity area (active crown fire or flame length > 3.4 m) of Restoration Unit 1 for July average wind conditions plus two standard deviations (21.6 kph at 178° azimuth) under the three treatment alternatives.

References

Ager, A.A., Vaillant, N.M., Finney, M.A., 2011. Integrating fire behavior models and geospatial analysis for wildland fire risk assessment and fuel management planning. J. Comb. 2011.
Calkin, D., Gebert, K.M., 2009. Economics of Wildland Fire Risk Management. Wildland Fire Lessons Learned Center.
Calkin, D.E., Gebert, K.M., Jones, J.G., Neilson, R.P., 2005. Forest Service large fire area burned and suppression expenditure trends, 1970–2002. J. For. 103 (4), 179–183.
Calkin, D.E., Cohen, J.D., Finney, M.A., Thompson, M.P., 2014. How risk management can prevent future wildfire disasters in the wildland-urban interface. Proc. Natl. Acad. Sci. 111 (2), 746–751.
Chazdon, R.L., 2008. Beyond deforestation: restoring forests and ecosystem services on degraded lands. Science 320 (5882), 1458–1460.
Cochrane, M.A., Moran, C.J., Wimberly, M.C., Baer, A.D., Finney, M.A., Beckendorf, K.L., Eidenshink, J., Zhu, Z., 2012. Estimation of wildfire size and risk changes due to fuels treatments. Int. J. Wildland Fire 21 (4), 357–367.
Covington, W.W., Moore, M.M., 1994. Southwestern ponderosa forest structure: changes since euro-American settlement. J. For. 92 (1), 39–47.
Crookston, N.L., Dixon, G.E., 2005. The forest vegetation simulator: a review of its structure, content, and applications. Comput. Electron. Agric. 49 (1), 60–80.
Cruz, M.G., Alexander, M.E., 2010. Assessing crown fire potential in coniferous forests of western North America: a critique of current approaches and recent simulation studies. Int. J. Wildland Fire 19 (4), 377–398.
Dixon, G.E., 2002. Essential FVS: A user's Guide to the Forest Vegetation Simulator. USDA-Forest Service, Forest Management Service Center, Fort Collins, CO.
Donovan, G.H., Rideout, D.B., 2003. A reformulation of the cost plus net value change (C + NVC) model of wildfire economics. For. Sci. 49 (2), 318–323.
Donovan, G.H., Noordijk, P., Radeloff, V., 2004. Estimating the impact of proximity of houses on wildfire suppression costs in Oregon and Washington. In: Proceedings of the Second International Symposium on Fire Economics, Planning, and Policy: A Global View.
Donovan, G.H., Prestemon, J.P., Gebert, K., 2011. The effect of newspaper coverage and political pressure on wildfire suppression costs. Soc. Nat. Resour. 24 (8), 785–798.
Finney, M.A., 1998. FARSITE users guide and technical documentation. In: USDA Forest Service Research Paper RMRS-RP-4.
Finney, M.A., 2004. FARSITE: Fire Area Simulator: Model Development and Evaluation. US Department of Agriculture, Forest Service, Rocky Mountain Research Station, Ogden, UT.
Finney, M.A., 2005. The challenge of quantitative risk analysis for wildland fire. For. Ecol. Manag. 211 (1), 97–108.
Finney, M.A., 2006. An overview of FlamMap fire modeling capabilities. In: Fuels Management – How to Measure Success: Conference Proceedings. 2006 March 28–30; Portland, Oregon. Proceedings RMRS-P-41 U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station, Fort Collins, CO, pp. 213–220.
Finney, M.A., McHugh, C.W., Grenfell, I.C., 2005. Stand-and landscape-level effects of prescribed burning on two Arizona wildfires. Can. J. For. Res. 35 (7), 1714–1722.
Fulé, P.Z., Waltz, A.E., Covington, W.W., Heinlein, T.A., 2001. Measuring forest restoration effectiveness in reducing hazardous fuels. J. For. 99 (11), 24–29.
Fulé, P.Z., Covington, W.W., Smith, H.B., Springer, J.D., Heinlein, T.A., Huisinga, K.D., Moore, M.M., 2002. Comparing ecological restoration alternatives: grand Canyon, Arizona. For. Ecol. Manag. 170 (1), 19–41.
Gebert, K.M., Calkin, D.E., Yoder, J., 2007. Estimating suppression expenditures for individual large wildland fires. West. J. Appl. For. 22 (3), 188–196.
Holmes, T.P., Huggett, R.J., Westerling, A.L., 2008. Statistical analysis of large wildfires.

In: The Economics of Forest Disturbances: Wildfires, Storms, and Invasive Species. Springer Science & Business Media, pp. 59–77.
Hurteau, M., North, M., 2009. Fuel treatment effects on tree-based forest carbon storage and emissions under modeled wildfire scenarios. Front. Ecol. Environ. 7 (8), 409–414.
Liang, J., Calkin, D.E., Gebert, K.M., Venn, T.J., Silverstein, R.P., 2008. Factors influencing large wildland fire suppression expenditures. Int. J. Wildland Fire 17 (5), 650–659.
Lynch, D.L., 2004. What do forest fires really cost? J. For. 102 (6), 42–49.
Monitoring trends in burn severity (MTBS), 2013. www.mtbs.gov/data/customquery.html (Last access 2016).
Pollet, J., Omi, P.N., 2002. Effect of thinning and prescribed burning on crown fire severity in ponderosa pine forests. Int. J. Wildland Fire 11 (1), 1–10.
Prestemon, J.P., Abt, K., Gebert, K., 2008. Suppression cost forecasts in advance of wildfire seasons. For. Sci. 54 (4), 381–396.
Radeloff, V.C., Hammer, R.B., Stewart, S.I., 2005a. Rural and suburban sprawl in the US Midwest from 1940 to 2000 and its relation to forest fragmentation. Conserv. Biol. 19 (3), 793–805.
Radeloff, V.C., Hammer, R.B., Stewart, S.I., Fried, J.S., Holcomb, S.S., McKeefry, J.F., 2005b. The wildland–urban interface in the United States. Ecol. Appl. 15 (3), 799–805.
Reinhardt, E.D., Keane, R.E., Calkin, D.E., Cohen, J.D., 2008. Objectives and considerations for wildland fuel treatment in forested ecosystems of the interior western United States. For. Ecol. Manag. 256 (12), 1997–2006.
Rideout, D.B., Wei, Y., Kirsch, A.G., Botti, S.J., 2008. Toward a unified economic theory of fire program analysis with strategies for empirical modeling. In: The Economics of Forest Disturbances: Wildfires, Storms, and Invasive Species. Springer Science & Business Media, pp. 361–380.
Roccaforte, J.P., Fule, P.Z., Covington, W.W., 2009. Assessing Changes in Canopy Fuels and Potential Fire Behavior Following Ponderosa Pine Restoration. Fire Management Today.
Ryan, K.C., Knapp, E.E., Varner, J.M., 2013. Prescribed fire in North American forests and woodlands: history, current practice, and challenges. Front. Ecol. Environ. 11 (s1).
Savage, M., Mast, J.N., 2005. How resilient are southwestern ponderosa pine forests after crown fires? Can. J. For. Res. 35 (4), 967–977.
Scott, J.H., Burgan, R.E., 2005. Standard fire behavior fuel models: a comprehensive set for use with Rothermel's surface fire spread model. Bark Beetles Fuels Fire Bibliogr. 66.
Scott, J.H., Reinhardt, E.D., 2001. Assessing crown fire potential by linking models of surface and crown fire behavior. In: Research Paper RMRS-RP-29. U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station, Fort Collins, CO 66 pp.
Stephens, S.L., 1998. Evaluation of the effects of silvicultural and fuels treatments on potential fire behaviour in Sierra Nevada mixed-conifer forests. For. Ecol. Manag. 105 (1), 21–35.
Stephens, S.L., Moghaddas, J.J., 2005. Experimental fuel treatment impacts on forest structure, potential fire behavior, and predicted tree mortality in a California mixed conifer forest. For. Ecol. Manag. 215 (1), 21–36.
Stephens, S.L., Moghaddas, J.J., Edminster, C., Fiedler, C.E., Haase, S., Harrington, M., Keeley, J.E., Knapp, E.E., McIver, J.D., Metlen, K., Skinner, C.N., 2009. Fire treatment effects on vegetation structure, fuels, and potential fire severity in western US forests. Ecol. Appl. 19 (2), 305–320.
Strategic Issues Panel on Fire Suppression Costs, 2004. Large fire suppression costs—strategies for cost management. In: Report to the Wildland Fire Leadership Council, (Unpublished report supplied by authors).
Stratton, R.D., 2004. Assessing the effectiveness of landscape fuel treatments on fire growth and behavior. J. For. 102 (7), 32–40.
Stratton, R.D., 2006. Guidance on spatial wildland fire analysis: models, tools, and techniques. In: General Technical Report RMRS-GTR-183. U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station, Fort Collins, CO 15 pp.
Swetnam, T.W., 1990. Fire history and climate in the southwestern United States. In: Proceedings of the Symposium on Effects of Fire Management of Southwestern United States Natural Resources. Gen. Tech. Rep. RM-GTR-191 US Department of Agriculture, Forest Service, Rocky Mountain Forest and Range Experiment Station, Fort Collins, CO.
Thompson, M.P., Vaillant, N.M., Haas, J.R., Gebert, K.M., Stockmann, K.D., 2013. Quantifying the potential impacts of fuel treatments on wildfire suppression costs. J. For. 111 (1), 49–58.
United States Department of Agriculture (USDA), Forest Service, Stockmann, K., Gebert, K., 2010. Wildland fire management Risk and Cost Analysis Tools package (R-CAT): User's Guide. CFLRP R-CAT User Guide. https://www.fs.fed.us/restoration/documents/cflrp/R-CAT/CFLRPWildifreR-CATUsersGuide01192011.pdf (Last access 2017).
United States Government Accountability Office (GAO), 2009. Wildland fire management: federal agencies have taken important steps forward, but additional, strategic action is needed to capitalize on those steps. In: Report to Congressional Addressees, GAO-09-877. www.gao.gov/assets/300/294742.pdf (Last access 2016).
United States Government Accountability Office (GAO), 2015. Wildland fire management: agencies have made several key changes but could benefit from more information about effectiveness. In: Report to Congressional Addressees, GAO − 15-772. www.gao.gov/assets/680/672579.pdf (Last access 2016).
United States Government Office of Policy Analysis (DOI), 2012. Wildland Fire Management Program Benefit-Cost Analysis A Review of Relevant Literature. www.doi.gov/sites/doi.gov/files/migrated/ppa/upload/Wildland_fire_literature_review_060812FINAL.pdf (Last access 2017).
Vaillant, N.M., Ager, A.A., Anderson, J., Miller, J., 2012. ArcFuels User Guide: For Use With ArcGIS 9.X. Internal Report. US Department of Agriculture, Forest Service, Pacific Northwest Research Station, Western Wildland Environmental Threat Assessment Center, Prineville, OR (Revised January 9, 2012). 247 pp.
Varner, J.M., Keyes, C.R., 2009. Fuels Treatments and Fire Models: Errors and Corrections. Fire Management Today.
Westerling, A.L., Hidalgo, H.G., Cayan, D.R., Swetnam, T.W., 2006. Warming and earlier spring increase western US forest wildfire activity. Science 313 (5789), 940–943.
Western Forestry Leadership Coalition, 2010. The True Cost of Wildfire in the Western U.S. www.wflcweb.org (Last access 2016).
Yoder, J., Gebert, K., 2012. An econometric model for ex ante prediction of wildfire suppression costs. J. For. Econ. 18 (1), 76–89.