Do Fuel Treatments Reduce Wildfire Suppression Costs and Property Damages? Analysis of Suppression Costs and Property Damages in U.S. National Forests¹

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Abstract

This paper reports the results of two hypotheses tests regarding whether fuel reduction treatments using prescribed burning and mechanical methods reduces wildfire suppression costs and property damages. To test these two hypotheses data was collected on fuel treatments, fire suppression costs and property damages associated with wildfires on United States National Forests over a five year period. Results of the multiple regressions show that only in California did mechanical fuel treatment reduce wildfire suppression costs. However, the results of our second hypothesis tests that fuel treatments, by making wildfires less damaging and easier to control, may reduce property damages (i.e., structures—barns, out buildings, etc. and residences lost) seems to be confirmed for acres treated with prescribed burning. In three out of the three geographic regions of the U.S. which experienced significant property losses, prescribed burning lowered the number of structures damaged by wildfire.

Keywords: mechanical fuel reduction, prescribed burning, property damage, wildfire suppression costs

¹ An abbreviated version of this paper was presented at the Fifth International Symposium on Fire Economics, Planning, and Policy: Wildfires and Ecosystem Services, November 14-18, 2016, Tegucigalpa, Honduras.

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Introduction

Around the world, large wildfires and fires in the wildland urban interface (WUI) have escalated in frequency, size, suppression costs and property damages. For example, during the last decade the USDA Forest Service (FS) alone has incurred wildfire suppression costs of over \$19 billion fighting wildfires that have burned more than 39 million ha of forest and brush lands (NIFC 2014). Furthermore, in the period from 1999 to 2010 more than 1100 homes were burned and a total of 230 lives lost (Gude et al. 2013). Additionally, there is growing recognition of the futility of fighting fires in ecosystems where prior fire exclusion policies have led to dangerous fuel accumulations. For example see GAO 2015 report (GAO: 1) which states ... " However, over the past century, various land management practices, including fire suppression, have disrupted the normal frequency of fires in many forest and rangeland ecosystems across the United States, resulting in abnormally dense accumulations of vegetation..." The 2014 Quadrennial Fire Review (Hamilton 2015: iii) further states that "... Fuel levels are also at unprecedented levels due to climatic change, decades of suppression that have limited fire from prewar levels of 25 to 40 million acres burned per year to 5 million or fewer since the 1960s, and a decline in active forest management..." One strategy for reversing this trend is to perform fuel reduction treatments such as prescribed burning and mechanical fuel reduction. In general, within the fire management community it is believe that such fuel reduction treatments, will be effective in reducing the wildfire suppression costs and property damage. This paper tests the hypotheses that current fuel treatment practices reduce wildfire suppression costs and property damage associated with wildfires on U.S. National Forests over the past five years.

Literature Review

By and large the three most common reasons found in the literature for explaining the current increase in wildfire property damages and suppression costs are: 1) fuels build up resulting in part from past fire suppression policies, 2) warmer temperatures and drought conditions, and 3) expansion of the WUI into fire-prone landscapes. We organize our literature review around these three reasons, although the emphasis is on 1 and 3 since these can be influenced by forest management.

From a theoretical perspective, Rideout et al. (2008) explored the topic of whether fuel treatments have the potential to reduce wildfire suppression costs in the treated area. They showed that it is difficult to establish an unambiguous relationship between fuel treatments and resulting suppression costs, without factoring in the implied level of net fire damage. Further, prior fuel treatments often make fire suppression efforts more effective, and hence more, not less, suppression may be

warranted in areas that have been treated, than in untreated areas (which may be too unsafe to engage in wildfire suppression or wildfire suppression will do little to reduce damages). On the other hand, because fire suppression may be more effective the resulting final wildfire size might be smaller, potentially reducing fire suppression costs and property damages. But what the net effect of these possible relationships are is an empirical question that can only be addressed with data on actual fire suppression costs in treated versus untreated areas. Therefore, we first turn to the existing literature to see what prior empirical analyses have found and to guide our empirical hypothesis testing.

A study of suppression costs in Western United States by Gebert et al. (2007), found that higher home values within 20 miles of a wildfire ignition increased suppression expenditures. All other variables that influenced suppression costs were biophysical variables like extreme fire behavior, drought conditions, wildfire intensity levels, and energy release component.

Yoder and Ervin (2012) were one of the first to conduct an analysis of fire suppression costs at the county level in the western U.S. and test whether there is any relationship between fuel treatment costs and wildfire suppression costs. To conduct this analysis, Yoder and Ervin ran suppression costs as a function of: acreage, prescribed (RX) burn acres, mechanically thinned acres, amount spent on RX burning, amount spent on thinning, vegetation type, WUI area, temperature, and precipitation.

Yoder and Ervin included four years of lagged values of burning acres and thinning acres to pick up relative effectiveness of these fuel treatments over time. While their model had reasonably high explanatory power (71% or .71 R²) generally neither the acres of prescribed burning nor the cost of prescribed burning nor the acres thinned nor the cost of thinning had a negative and significant effect on suppression costs (just one of the 16 variables). However, it is possible that their model exhibits a degree of multicollinearity; as one would expect that acres thinned and cost of thinning as well as acres burned and cost of burning would be highly correlated, and thus this could mask a significant relationship.

More recently, Gude et al. (2013) used fires in California's Sierra Nevada to estimate the relationship between housing and fire suppression costs. That is, whether the presence of homes is associated with increases in fire suppression costs after controlling for other biophysical parameters (e.g., size, terrain, weather, etc.). Their study found a small, but statistically significant increase in suppression costs with the presence of homes within a 6-miles radius of an active wildfire. Scofield et al. (2015) analyzed the effect of the spatial configuration of houses in the WUI on costs of fighting nearly 300 wildfires in Colorado, Montana and Wyoming from 2002 to 2011. Schofield et al. (2015: 3) found that not only does homes in the WUI matter,

but that whether the homes are widely dispersed in that landscape (e.g., 35 acre parcel development common in Colorado) versus whether they are clustered together had a significant effect on wildfire suppression costs. Gude et al. (2014) evaluated the factors determining fire suppression costs including the Firewise Program. In their model the fire size, fire duration and terrain difficulty had the biggest influence on fire suppression costs. The Firewise Program variable was not significant.

Finally, Thompson and Anderson (2015) took a modeling approach to evaluating the effects of fuel treatment on fire suppression costs. They compared three modeling approaches that were applied in different geographic areas (i.e., Oregon, Arizona and the Great Basin). Across this broad geographic span they found that the potential existed for costs of fighting wildfires to be reduced by fuel treatments. However, they noted (Thompson and Anderson, 2015: 169): "Second, the relative rarity of large wildfire on any given point on the landscape and the commensurate low likelihood of any given area burning in any year suggests the need for large-scale fuel treatments....Thus in order to save large amounts of money on fire suppression, land management agencies may need to spend large amounts of money on large-scale fuel treatment". This will be a point we return to in our conclusion.

What can we conclude from the literature? First, in order to isolate the effect of fuel treatment on wildfire suppression costs, it is important to control for whether the wildfire was in WUI and biophysical variables. Specifically, wildfire suppression costs were related to fire size, terrain (e.g., slope), and wildfire intensity levels. Higher fuel loads (e.g., density and type of vegetation) also appear to affect wildfire suppression cost, and reducing fuel loading is one of the purposes of prescribed burning and mechanical fuel treatments. Thus, our empirical model specification includes all of these factors in an attempt to control for them when testing whether fuel reduction treatment reduces wildfire suppression costs.

Fuel treatments are increasing viewed as a means to reduce the severity of wildland forest fires, and make these fires easier to control and suppress. An ancillary goal is to reduce property damages and lives lost due to wildfires. While these are desirable goals of a fuel treatment program, prescribed burning and mechanical fuel reduction are costly to conduct. As such they have to be budgeted for. In order to budget for them, it is necessary to have some systematic method to estimate the costs.

Empirical Model Specification and Hypothesis Tests

Wildfire Suppression Cost Model

Building upon the Gude (2014) and Yoder and Ervin's (2012) models, particularly in the latter, we estimate a multiple regression model to test hypotheses and quantify the effect of fuel treatment efforts on wildfire suppression costs and structures damaged.

Our regression models account for many of the quantitative and qualitative variables that influence the costs of wildfire suppression costs. In particular:

Dependent Variable

Ln(TSC) = natural log of Total Suppression Costs

Independent Explanatory Variables

Acres_Mech: Acres of the wildfire area with prior mechanical fuel treatment

Acres_RX: Acres of the wildfire area with prior fire fuel treatment

InWFacres: natural log of wildfire size in acres

WUIY: intercept shifter variable for whether the fire is in a WUI area

Elev: average elevation of the wildfire area

Slope: average slope within the wildfire area

% low fuel load: percent of the area with low level of existing fuel loads

% mixed fuel load: percent of the area in medium or mixed level of existing fuel loads

% high fuel load: percent of the area in high level of existing fuels (omitted dummy)

FInt_ft: Fire Intensity Level, measured in feet

Crown Density: Crown bulk density

Fire Return Interval: Mean Fire return interval of the vegetation across the wildfire area

Interaction Term

WUIY * **Elev**: included to see if there was a differential cost of fighting wildfires in WUI areas as the elevation increased.

The baseline model specified for all geographic regions (defined in more detail below) is:

 $(1) ln(TSC) = B_0-B_1(Acres_Mech) - B_2(Acres_RX) + B_3(lnWFacres) + B_4(WUIY) \\ + B_5(Elev) + B_6(Slope) - B_7(\%low fuel load) + B_8(\%mixed fuel load) + B_9(FInt_ft) \\ + B_{10}(Crown Density) + B_{11}(Fire Return Interval) + B_{12}(WUIY*Elev)$

The coefficients on the fuel treatment variables should be negative and significant if presuppression fuel treatment reduces fire suppression costs.

Mathematically our hypothesis (with TSC as dependent variable) can be expressed as:

- (2) Ho: $B_{AcresRX} = 0$ Ha: $B_{AcresRX} < 0$
- (3) Ho: $B_{AcresMECH} = 0$ Ha: $B_{AcresMECH} < 0$

The hypotheses are tested based on asymptotic t-statistics on the two types of pre-suppression fuel treatments.

Property Damage Model

(2) $ln(\#Structures) = A_0-A_1(Acres_Mech) -A_2(Acres_RX)+A_3(lnWFacres) +A_4(WUIY)$

Where #Structures is the sum of houses and other structures (barns, out buildings, unattached garages, etc.) destroyed by wildfires.

The hypothesis tests for property damage (# structures) is:

(4) Ho: $A_{AcresRX} = 0$ Ha: $A_{AcresRX} < 0$ (5) Ho: $A_{AcresMECH} = 0$ Ha: $A_{AcresMECH} < 0$

The hypotheses are tested based on asymptotic t-statistics on two types of presuppression fuel treatments.

Data

Study Sites

To make the study as comprehensive as possible and representative of all vegetation types and fuel models, and fuel treatment activities across the U.S. we collected fuel treatment and wildfire suppression costs and associated data in all U.S. National Forest regions of the continental U.S. except Alaska. Ecologically, and in terms of its fire regime, Alaska is very different from all regions in the continental US that it would require a separate modeling effort.

Development of Database for Wildfire Suppression Costs

Individual wildfire suppression data was obtained for years 2010 to 2014. This file includes data on the size of each fire, structures destroyed, and of course the cost of suppression. However, there were significant concerns regarding the accuracy of the cost data reported, especially for small fires. A significant effort was made to collaborate with the USDA Forest Service scientists at the Rocky Mountain Research Station to obtain more accurate wildfire suppression cost data for large wildfires (fires greater than 300 acres). Thus we restrict our analysis to fires 300 acres or larger. This more accurate cost of suppression data was obtained and merged into the other wildfire suppression data describing wildfires to create a master wildfire suppression database where the unit of analysis is the individual fire.

Data on RX burning and mechanical fuel treatment was obtained from the USDA Forest Service FACTS treatment area data. Acres treated by each method were geolocated and then merged into the wildfire suppression cost data and the GIS spatial data on the area of the treatments and wildfires (e.g., slope, elevation, vegetative cover) to create the master dataset used for the regression analysis.

Determining Geographic Regions of Analysis

Given the limited number of observations for each of the USDA Forest Service Regions, we evaluated grouping the data into larger geographic regions. A natural choice for this was the U.S. interagency Geographic Area Coordination Centers (GACC) used by the Forest Service fire management organization for making fire suppression decisions, including logistics and dispatch. An initial national wildfire suppression cost model was estimated that included each GACC as an intercept shifter variable to allow evaluation of the similarity of geographic regions' coefficients. In addition, an ANOVA (Analysis of Variance) was performed on the individual GACC's that showed that some GACC's had statistically significant differences in wildfire suppression costs per acre from each other but others did not. Based on these two statistical analyses as well as geography, the GACC's were put into groups of two or three. Specifically, the Northern and Southern California GACC's were made into one fire suppression cost analysis area. The Eastern and Southern GACC's were also combined. The two Rocky Mountain GACC's and the Southwest GACC were combined into one wildfire suppression analysis area. The Northwest GACC and Great Basin GACC's were combined. Thus we have four wildfire analysis regions. Details on the national wildfire suppression cost model and the ANOVA is available from the senior author.

Selected Descriptive Statistics

Table 1 provides the key descriptive statistics on the number of wildfires, structures destroyed and the average percentage of a wildfire area treated with RX fire and mechanical fuel reduction treatments. As can be seen in Table 1, only small percentages of wildfire areas have had fuel treatments. As can be seen by comparing the mean and median, far less than half the areas had any fuel treatments of any kind.

It is also worth noting that there is insufficient sample size to estimate a regression on structures and houses lost in wildfires with and without treatment for the Eastern and Southern GACC. Specifically, there were only eight structures lost in total in two of the 173 wildfires in the Eastern and Southern GACC.

Table 1. Percent of Wildfire Areas Treated and Structures and Houses Destroyed

GACC Group	Percent Treated		Number Destroyed		Sample
Wildfires	Fire	Mechanical	Structures	Houses	n
Group 1 East-SO					
Mean	15	0.5	6	2	173
Median	0	0			
Group 2 Rocky-SW					
Mean	8.8	0.4	36	20	390
Median	0	0			
Group 3NW-GB					
Mean	7.3	0.5	35	9	223
Median	0	0			
Group 4 California					
Mean	1	0.13	27	19	115
Median	0	0			

East-So is the Eastern and Southern GACCs; Rocky-SW is the Rocky Mountains and Southwest GACCs. NW-GB is the Northwest and Great Basin GACCs. Calif is the Northern and Southern California GACCs.

Results

Statistical Results of Wildfire Suppression Cost by GACC Groups

In Table 2 we presents the regression results for Group #1 (Eastern and Southern GACC's)

Table 2. Suppression Costs for GACC Group #1 (Eastern and Southern GACC's).

Variable	Estimate	Std. Error	t value	Probability
Intercept	2.6553	1.1021	2.409	0.1712*
Acres_Mech	-0.1913	0.6397	-0.299	0.7653
Acres_RX	-0.0004	0.0004	-1.227	0.2216
lnWFacres	0.9930	0.1358	7.312	1.17e-11***
WUIY	0.8679	0.3539	2.452	0.01526*
Elevation	-0.0015	0.0006	-2.439	0.01058*
Slope	0.1215	0.0264	4.603	8.40e-06***
% low fuel load	-0.0008	0.0333	-0.023	0.982
% mixed fuel load	-0.0650	0.0498	-1.305	0.1939
FInt_ft	0.0848	0.0308	2.753	0.00658**
Crown density	0.1784	0.0835	2.136	0.0342*
Fire Return Interval	0.0810	0.0442	1.833	0.0687.
WUIY*Elevation	0.0001	0.0001	0.125	0.9007
R square	0.4920			

^{***} significant at the 99.99% level; ** significant at the 99.9%; * significant at the 99% level;

⁺ significant at the 95% level; . significant at the 90% level.

Most of the variable coefficient signs make sense: wildfires involving WUIY, higher crown density forests, steeper slopes and high fire intensity levels have greater than average suppression costs. Overall the model's explanatory power is reasonably good (49.2%) for cross section data across a broad a geographic scope.

In terms of our hypotheses tests, neither Acres Mech treatment nor Acres RX treatment are statistically different from zero. That is, acres of the wildfire area treated with either mechanical or fire fuel treatments appear not to have a systematic effect on wildfire suppression costs.

Table 3 presents the regression results for the model for Group 2 (Rocky Mountains and Southwest GACC's).

Variable	Estimate	Std. Error	t-value	Probability
Intercept	5.0260	0.6357	7.905	2.93e-14 ***
Acres_Mech	0.5056	0.4550	1.111	0.267156
Acres_RX	0.0000	0.0002	0.214	0.830862
lnWFacres	0.5318	0.0760	6.997	1.18e-11 ***
WUIY	2.3740	0.9269	2.562	0.010806 *
Elevation	0.0010	0.0002	3.923	0.000104 ***
Slope	0.0518	0.0159	3.264	0.001197 **
% low fuel load	0.0094	0.0189	0.499	0.617967
% mixed fuel load	0.0302	0.0317	0.952	0.341547
FInt_ft	0.1638	0.0229	7.141	4.74e-12 ***
Crown density	-0.0221	0.0306	-0.724	0.46943
Fire Return Interval	-0.0585	0.0240	-2.440	0.015150 *
WUIY*Elevation	-0.0007	0.0005	-1.488	0.137542
R square	0.425			

^{***} significant at the 99.99% level; ** significant at the 99.9%; * significant at the 99% level; + significant at the 95% level; . significant at the 90% level;

Most of the variable coefficient signs in Table 3 make sense: wildfires involving WUIY, steeper slopes, higher elevation and higher Fire Intensity level all result in higher than average wildfire suppression costs. The explanatory of the model is fairly high (42.5%) for cross section data across such a broad geographic scope.

In terms of our hypotheses tests, Acres Mech Treatment and Acres RX Treatment are not statistically different from zero. That is, acres of the wildfire area treated with either mechanical or fire fuel treatments appear not to have a systematic effect on wildfire suppression costs.

Table 4 presents the regression results for the model for Group 3 (Northwest and Great Basin GACC's).

Table 4. Suppression Costs for GACC Group #3 (Northwest and Great Basin GACC's).

/ariable	Estimate	Std. Error	t-value	Probability	
Intercept	8.9760	0.8400	10.686	2e-16 ***	
Acres_Mech	-0.1818	0.5090	-0.357	0.7213	
Acres_RX	0.0001	0.0003	0.247	0.8054	
lnWFacres	0.5529	0.0904	6.114	4.74e-09 ***	
WUIY	-0.1205	0.7861	-0.153	0.8783	
Elevation	0.0001	0.0002	0.358	0.721	
Slope	0.0065	0.0174	0.371	0.7109	
% low fuel load	0.0215	0.0327	0.657	0.5118	
% mixed fuel load	0.0229	0.0364	0.63	0.5294	
FInt_ft	0.0262	0.0313	0.837	0.4035	
Crown density	0.0630	0.0268	2.351	0.0197 *	
Fire Return Interval	-0.0597	0.0272	-2.198	0.0291 *	
WUIY*Elevation	0.0005	0.0005	1.15	0.2513	
R square	0.26				

^{***} significant at the 99.99% level; ** significant at the 99.9%; * significant at the 99% level; significant at the 95% level;

The performance of this model is relatively low with wildfire size, higher crown density and longer fire return interval resulting in higher than average wildfire suppression costs. The explanatory power of the Pacific Northwest and Great Basin model is 25%.

In terms of our hypotheses tests, neither Acres Mech nor Acres RX are statistically different from zero. That is, acres of the wildfire area treated with either mechanical or fire fuel treatments appear not to have a systematic effect on fire suppression costs.

Table 5 presents the regression results for the model for Group #4 Northern and Southern California.

Variable	Estimate	Std. Error	t-value	Probability	
Intercept	9.6310	1.0980	8.772	4.21e-14 ***	
Acres_Mech	-4.2690	2.1490	-1.987	0.04963 *	
Acres_RX	0.0000	0.0001	-0.326	0.74547	
lnWFacres	0.5859	0.1096	5.344	5.56e-07 ***	
WUIY	-0.9208	0.8329	-1.106	0.27148	
Elevation	-0.0003	0.0004	-0.805	0.42269	
Slope	0.0257	0.0229	1.121	0.26488	
% low fuel load	0.0302	0.0289	1.044	0.29918	
% mixed fuel load	0.0907	0.0490	1.85	0.06725 .	
FInt_ft	0.0652	0.0350	1.864	0.06526.	
Crown density	0.0122	0.0341	0.358	0.72117	
Fire Return Interval	-0.1130	0.0414	-2.731	0.00745 **	
WUIY*Elevation	0.0006	0.0008	0.822	0.41309	
R square	0.49				

^{***} significant at the 99.99% level; ** significant at the 99.9%; * significant at the 99% level;

The California regression performs reasonably well in terms of signs and significance level. In particular the variable coefficient signs make sense: high percent mixed fuel load fuels, higher fire intensity level, and the longer the fire return interval results in higher than average wildfire suppression costs. We believe that WUIY is insignificant because there is little variation, as most wildfires in California have a WUIY area within them. The explanatory power of the model is reasonably good at 49%.

In terms of our hypotheses tests, the statistical significance and negative sign on Acres Mech indicates that the more acres of a wildfire area treated with mechanical fuel reduction, the lower the costs of fire suppression in California. However, Acres RX is not statistically different than zero. That is, acres of the wildfire area treated with a fire fuel treatment appear not to have a systematic effect on wildfire suppression costs.

Out of the four GACC groups, only one of the fuel treatments had a statistically significant negative effect on wildfire suppression costs (Northern and Southern California GACCs). As noted above in our discussion of hypotheses, it is possible that the lack of statistical significance of the fuel treatment variables may be due to opposing effects: in some wildfires, fuel treatment did lower suppression costs, but in other wildfires, fuel treatments allowed fire fighters to enter areas that would otherwise not be safe, thereby raising wildfire suppression costs. As Rideout et al. (2008) point out this is result is theoretically possible under plausible circumstances. In addition as noted by Thompson and Anderson (2015) there may simply be too few

⁺ significant at the 95% level; significant at the 10% level $R^2 = 49.0\%$

fuel treatments in areas with wildfires to detect any effects of fuel treatments on wildfire suppression costs. That lack of significance of prescribed burning (Acres_RX) and mechanical fuel reduction (Acres_Mech) almost uniformly across all but one GACC regions is consistent with the findings of Yoder and Ervin (2012). Our results are also consistent with the general finding of Gude et al. (2014) that the Firewise Communities Program of reducing vegetative fuels around homes did not reduce wildfire suppression costs.

Results for Effect of Fuel Treatment of Property Damages

Our second hypothesis test is that fuel reduction treatments such as RX burning and mechanical fuel reduction by raising the marginal productivity of a given expenditure of fire suppression money would reduce the number of homes and other structures damaged by wildfires (Rideout et al. 2008). This is the finding of Bostwick et al. (2011) for one fire (Wallow Fire) in the southwestern U.S. Obviously testing with multiple fires in multiple geographic regions is necessary to determine if this is the usual result or not.

As was shown previously in Table 1, the relatively low number of structures (i.e., houses, barns, out buildings) damaged relative to the large number of fires suggested that a count data model might be the appropriate statistical technique to estimate the effect of fuel treatments on property damages. A count data is well suited to handle small integers, including zeros better than OLS regression does. We adopted a rather parsimonious model to test for the effect of the number of acres of the wildfire treated with mechanical fuel reduction (Acres_Mech) and the number of acres treated with prescribed fire fuel treatment (Acres_RX). Other variables included are size of wildfire (lnWFacres) and whether the fire occurred in a WUI area. Due to the fact that GACC Group #1 only had 2 homes lost and 6 other structures destroyed out of 173 wildfires, it was determined that it was not feasible to estimate a count data model regression for GACC Group #1.

The results in Table 6 across the three GACC groups with sufficient data on structures burned, show that larger wildfires and wildfires in WUI resulted in more structures lost. In terms of our hypothesis, the larger the wildfire area treated with prescribed burning the fewer the number of structures destroyed. Specifically, in all three GACC's the coefficient on Acres_RX is negative and statistically significant, indicating as Acres RX went up, number of structures destroyed decreased (all were

significant at the 99% level). The results were more mixed for mechanical fuel reduction. In GACC Group #2 (the Rocky Mountains and Southwest) Acres_Mech was positive and significant at the 95% level. In the Northwest and Great Basin (GACC Group #3) Acres_Mech was negative but not significant at conventional levels.

Table 6. Count Data Regression Results for Number of Structures Destroyed in Wildfires

Table 6a. GACC Group #2 (Rocky Mountains and Southwest GACC's).

	Coefficients Estimate	Std. Error	t-value	Probability
Intercept	-8.364	0.5040	-16.594	< 2e-16 ***
lnWFacres	0.8113	0.0506	16.032	< 2e-16 ***
WUI	1.483	0.1577	9.406	< 2e-16 ***
acres RX	-2.494e-04	8.795e-05	-2.835	0.0046 **
acres_Mech	0.5697	0.2949	1.932	0.0533.

Significance codes: 0.0001***; 0.001**; 0.05.

Table 6b. GACC Group #3 (Northwest and Great Basin GACC's).

	Coefficients Estimate	Std. Error	t-value	Probability
Intercept	-6.8109	0.4335	-15.713	< 2e-16 ***
lnWFacres	0.7159	0.0426	16.814	< 2e-16 ***
WUI	1.4699	0.1372	10.711	< 2e-16 ***
acres RX	-0.0013	0.0004	-3.472	0.0005 ***
acres_Mech	-0.4496	0.4387	-1.025	0.3055

Significance codes: 0.0001***

Table 6c. GACC Group #4 (Northern and Southern California GACC's).

	Coefficients Estimate	Std. Error	t-value	Probability
Intercept	-4.8659	0.2750	-17.694	< 2e-16 ***
lnWFacres	0.6749	0.0297	22.739	< 2e-16 ***
WUI	0.7749	0.1089	7.108	1.18e-12 **
acres RX	-0.0291	0.0038	-7.737	1.01e-14 **
acres_Mech	4.8093	1.3655	3.522	0.0004 ***

Significance codes: 0.0001***

Conclusion

Overall we found that fuel treatments rarely had a significant effect on reducing wildfire suppression costs. As noted in the literature (particularly Thompson and Anderson, 2015), it may be that for fuel treatments to have a significant effect on wildfire suppression costs, there has to be a more substantial effort on prescribed burning and mechanical fuel reduction than is currently the case. Alternatively, as pointed out by Rideout et al. (2008) fuel treatments may increase the effectiveness of wildfire suppression efforts leading to reduced resource and property damages. In the case of property damages, Rideout et al. (2008) hypothesis seems borne out. In our data, areas with prescribed burning did have lower property damages from wildfires. This may suggest emphasizing presuppression fuel reduction in WUI areas as the primary benefits of such fuel reduction projects is in reducing property damages rather than reducing wildfire suppression costs. But this evidence should be revisited after data on the 2016 wildfire season is available, since 2016 had a substantial number of homes lost compared to what is in our data set.

Of course all research conclusions are subject to limitations, and ours is no exception. As noted in the data section, we focused on fires of 300 acres and larger as we were told by fire management personnel this was the best quality data available on fire suppression costs and that fire suppression cost data on smaller fires was not reliable. It is possible that with data on a wider range of fire sizes (e.g., fires of 50 acres and larger) that there may be more of an effect of presuppression fuel treatments in reducing fire suppression costs.

In addition, the current research results also suggest a new hypothesis. Specifically, that one potential effect of presuppression fuel treatments may be to keep small fires from growing into larger, more expensive to control fires. Unfortunately we do not have data to test this hypothesis but it seems like this may be an important avenue for future research, if the quality of fire data on small fires is improved in the future.

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