Do fuel treatments reduce wildfire suppression costs and property damages? Analysis of suppression costs and property damages in U.S. National Forests

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Abstract

This paper tests two hypotheses on whether fuel reduction treatments (prescribed burning and mechanical methods) reduce wildfire suppression costs and property damages. Data were collected on fuel treatments, fire suppression costs and property damages associated with wildfires on United States National Forests over a five year period throughout the continental U.S. Results of the multiple regressions in seven geographic regions of the U.S. show that only in California did mechanical fuel treatments reduce wildfire suppression costs. The second hypothesis test is that fuel treatments, by making wildfires less damaging and easier to control, may reduce property damages (i.e., structures—barns, out buildings, and residences lost). This hypothesis is generally confirmed for hectares treated with prescribed burning in four out of five geographic regions that had a significant coefficient on prescribed fire. Mechanical fuel reduction had a significant negative effect in reducing property damages in two of the three regions with a significant coefficient on mechanical fuel treatment.

Keywords: count data model, mechanical fuel reduction, prescribed burning

1. 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 (USDA FS) has incurred wildfire suppression costs of over $19 billion fighting wildfires that have burned more than 39 million hectares of forest and brush lands (NIFC, 2016). Further, in the period from 1999 to 2010 more than 1,100 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. 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 believed that such fuel reduction treatments, will be effective in reducing wildfire suppression costs and property damage. This paper tests these two 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.

1.1 Literature Review

1.1.1 Determinants of Fire Suppression Expenditures and the Effectiveness of Fuel Treatments.

The three most common reasons found in the literature for explaining the current increase in wildfire suppression costs are: 1) build-up of fuels 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 and land use planning.

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 meaning that they often increase the marginal productivity of suppression. 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). Alternatively, because fire suppression may be more effective, the final wildfire size might be smaller, potentially reducing fire suppression costs and property damages. The net effect of these possible relationships 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 models.

The empirical literature on this topic can be grouped by the original purpose of the research. Some models are designed primarily to determine factors influencing overall fire suppression expenditures or to forecast overall fire suppression expenditures. Some models are designed to test whether fuel treatments reduce wildfires. Fewer articles address whether fuel treatments reduce suppression expenditures. We review all three types as they all provide different insights to our empirical problem of estimating the effect of fuel treatments on fire suppression costs. Given the volume of literature on these topics, especially whether fuel treatments reduce wildfire itself, our review is not an exhaustive review of all the articles published on these broad topics, as that is not our purpose here. Rather, we provide the reader with an understanding of how our paper advances the existing literature, why we choose the independent variables we did, and how our results compare to what others have found on topics most closely related to ours.

The empirical literature regarding the determinants of suppression costs suggests a wide range of factors are at play. For example, 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. 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. Liang et al. (2008) evaluated suppression costs of the USDA FS for a 100 wildfires in the Northern Rockies from 1996 to 2005. Besides size of the fire and perimeter to area ratio, the next most important variables were percentage of private land in the area and total structure value with the remaining 12 biophysical variables such as slope, elevation and aspect contributing much less explanatory power. 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. Scofield et al. (2015) found that not only do 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.

Abt et al. (2009) used a time series regression to forecast fire suppression expenditures for entire National Forest Regions or groups of Regions (what they called their Western Aggregate). Other than lagged suppression costs, this model primarily included weather/climate related variables. Yoder and Gebert (2012) develop an econometric model for prediction of wildfire suppression cost. This model uses the same source of USDA FS data as we do in terms of fires 300 acres (121 hectares) or larger, and many of the same control variables (e.g., elevation of the fire and slope) but since they are not testing for whether fuel reduction reduces treatment cost, their models do not include variables for whether the fire area had been subject to prescribed fire or mechanical fuel reduction efforts. Their results also indicate housing values influence suppression cost, and that elevation and slope of the fire area influences costs as well.

Hand et al. (2016) conduct an econometric analysis of wildfire suppression cost expenditures using data on fires 300 acres (121 hectares) or larger in the western U.S. The goal of their analysis is to relate federal suppression expenditures to a set of biophysical variables including elevation, energy release component (i.e., fuel moisture), slope, vegetation type, house values, aspect, geographic dummy variables and year indicator variables. They find that spatial and temporal variations in several of these variables matter in terms of statistical significance and improved model prediction of suppression expenditures. However, slope and aspect did not. Further, their models do not explicitly account for fuel treatments that occurred in the perimeter of the wildfire burn area.

The literature most closely related to the purpose of our research includes papers by Cochrane et al. (2012), Parks et al. (2015), Butry (2009), Moghaddas and Craggs (2007), Thompson and Anderson (2015), Yoder and Ervin (2012), Fitch et al. (2017) and Vaillant and Reinhardt (2017). Cochrane et al. (2012) investigated the effect of 1,300 individual fuel treatments on 14 large wildfires using a simulation approach. They calibrated a simulation model to these 14 large wildfires that had been treated and then used the model to simulate what would have been the fire behavior had these areas not been treated. They conclude that fuel treatments in these 14 large wildfires would have changed fire spread rates and reduced the likelihood of fire crowning behavior. They indicate that much larger samples are needed. However, their study was not intended to nor did they analyze the relationship between fuel treatments and suppression cost. Nonetheless, fire spread rates and crowning behavior tend to influence fire suppression costs (Moghaddas and Craggs, 2007). Parks et al. (2015) studied the role that previous wildfires played in limiting the progression of subsequent wildfires. In essence the prior wildfire acted as a proxy for fuel treatments. The authors found that prior wildfires did limit the subsequent spread of wildfire in all four of their study areas under moderate weather conditions. This provides some evidence for the effectiveness of fuel treatments in reducing fire spread, and at least in moderate weather conditions, and thus likely reduced fire suppression costs as well (Moghaddas and Craggs, 2007). Thompson and Anderson (2015) also took a modeling approach but they did so to evaluate 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".* But, Reinhardt et al. (2008) believe the inability to know where the few large and expensive to suppress fires will occur suggest that such widespread fuel treatments might only reduce fire suppression expenditures if used in conjunction with controlling residential development in fire-prone areas and a tempering of the "all-out" approach to fire suppression. Otherwise, they feel it may be a mistake to think that fuel treatments by themselves can reduce wildfire suppression expenditures. Much like Thompson and Anderson (2015), Vaillant and Reinhardt (2017) and Barnett et al. (2016) both find a relative rarity of the intersection of fuel treatments and wildfire on federal lands in the same coterminous U.S. area we study. In the face of this rarity, Barnett et al. (2016) emphasizes the need to prioritize fuel reduction projects. An example of such prioritization is Jones et al. (2017) where the focus on fuel treatments is on accessible portions of urban watersheds.

Butry (2009) utilized a propensity scoring method to analyze the effect of prescribed fire on what they refer to as wildfire-intensity weighted acres. The author makes the case that propensity scoring has advantages over OLS regression when there may be unobservable variables, and these unobservable variables are correlated with the prescribed fire fuel treatment. Unfortunately he does not compare the propensity scoring approach to OLS for his data, but he suggests OLS models may underestimate the impact of prescribed fire. Nonetheless, even using a propensity scoring model with his fine scale spatial data for the St. Johns River Water Management District in northeast Florida, he finds that in only one of the nine comparisons does prescribed fire reduce wildfire intensity-acres at the 5% level (another one is what he labels “weakly significant” at the 11% level). The largest effect is that a 1% increase in prescribed fire reduces wildfire intensity-acres by 0.0436%, and the average effect across the entire sample is 0.0138%. Thus, even when statistically significant, the effect of fuel treatments is very small.

Moghaddas and Craggs (2007) studied the effect of a small 1-year old mechanical fuel treatment that was on private land that happened to be adjacent to an untreated area of the Plumas National Forest in California during a wildfire on the Plumas National Forest. The presence of this fuel treatment reduced the fire severity, increased suppression effectiveness, and reduced suppression costs.

Fitch et al. (2017) has an intermediate size analysis area of five National Forests in northern Arizona dominated by Ponderosa Pine. They focus on fires 324 hectares and larger. Their wildfire suppression cost regression model includes as explanatory variables the dominant vegetation cover, wildfire size, and distance to WUI areas. Their dependent variable used a natural log transformation of wildfire suppression cost per hectare. Their results indicate that the farther the wildfire area was from WUI areas, the lower the wildfire suppression costs. In their modeling effort the fuel treatments worked through reducing the proportion of wildfire burning at high severity and mixed severity. A 1% increase in proportion of the wildfire burning at high and mixed severity increased wildfire suppression costs by 6.43% and 4.91% relative to low severity.

Yoder and Ervin (2012) were one of the first to directly test the effect of fuel treatments on fire suppression costs at the county level in the western U.S. To conduct this analysis, the authors ran the natural log of total suppression costs at the county level as a function of: wildfire acreage, prescribed (RX) burn acres, mechanically thinned acres, amount spent on RX burning, amount spent on thinning, vegetation type, WUI area, temperature, and precipitation. While their model had good explanatory power (R^2=0.71) neither the acres of prescribed burning, the cost of prescribed burning, acres thinned, the cost of thinning had a negative and significant effect on 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.

Several inferences can be made from this literature. First, 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 thus 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 treatments reduces wildfire suppression costs.

In contrast to Yoder and Ervin (2012) who use county averages, our analyses use individual fire level data. This provides a finer geographic resolution than using counties as a unit of analysis. The previous literature on the effect of fuel treatment on wildfires that have used individual fire data have focused on fairly small geographic areas (e.g., one county or water district in Florida), and as such limits the geographic generalizability of their findings. We have been able to do our analysis at the individual fire level for the entire National Forest System (excluding Alaska and Hawaii). Nonetheless, being nationally comprehensive down to the individual fire level requires that we use what data is consistently available nationwide. Thus, not every variable that every paper has included can be included in our analysis. Nevertheless, the broader geographical generalizability of our results fill an important gap in the fuel treatment-wildfire suppression cost analysis literature.

1.1.2 Determinants of Residences and Structures Destroyed by Wildfire.

Our second hypothesis test is that fuel reduction treatments, such as prescribed burning and mechanical fuel reduction, raise the marginal productivity of a given expenditure of fire suppression and 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 assess the broader applicability of their result.

There are, of course, several factors that influence the number of houses and other structures (e.g., barns, equipment sheds, etc.) destroyed by wildfires. Certainly one key one is the flammability of building materials used in the home (Cohen, 2000; Calkin et al. 2014). The land use configuration matters—aka the WUI problem, as pointed out by Calkin et al. (2014). Vegetation matters, including vegetation in the immediate "home ignition zone" (Calkin et al. 2014) which involves "defensible space" around the home, especially within 5-20 meters (Spyhard et al. 2014). Our focus in this paper is on vegetation management on National Forests that often surround many WUI communities throughout the U.S. Specifically we evaluate the effect prescribed burning and mechanical fuel reduction treatments on reducing the number of homes and other structures destroyed by an individual wildfire, controlling for the presence of WUI, slope, elevation and type of fuels in the area. We take as given the flammability of homes and other structures, and the degree to which the homeowners have conducted Firewise treatments immediately around their homes (i.e., in the home ignition zone). While evaluating the effectiveness of Firewise treatment is itself an important area of research it is not the purpose of our paper. For those interested in this topic we recommend Cohen (2010) and Evans et al. (2015).

2. Empirical Model Specification and Hypothesis Tests

2.1 Wildfire Suppression Cost Model

Building upon the available literature, 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 but not all of the quantitative and qualitative variables that may influence the costs of wildfire suppression. As detailed below our final empirical model incorporates size of the wildfire, whether the wildfire is in a WUI area, the average elevation and slope of the wildfire area, and of course the acreage of the wildfire area treated with mechanical and prescribed fire. Many other variables were initially identified, included in our preliminary model and were initially tested for individual significance (i.e., their t-statistic) and contribution to overall model performance (i.e., the model AIC). These variables include crown bulk density, fire intensity level, percent mixed severity fires, and fire return interval. Acres of the wildfire in Wilderness were zero in three of our geographic regions used in the analysis so it was not included. We did not collect data on fire duration, which is an omission that may reduce our overall explanatory power of regressions. Ideal fire suppression cost models would also incorporate weather during the fire. We did not pursue obtaining that data as with 900 individual fires across the nation that would be an effort well beyond the budgetary resources and timeline of the project. Fire duration and wildfire weather would be an important variable for future research to test as the fires in California during the fall of 2017 suggests weather can be a significant factor influencing wildfire costs.

There were trade-offs in how to define the dependent variable. Hand et al. (2016) used total suppression cost as the dependent variable and included an explanatory variable for total size of the wildfire. While we initially tried this specification, we chose the natural log of the suppression cost per hectare to deal with any potential for heteroscedasticity across fires of quite different sizes that might be a problem had we used total suppression cost (the R squares using total suppression cost along with total wildfire size as a RHS variable gave us a much higher R square, but given our concern for heteroscedasticity we opted for the cost per hectare specification—results of the total wildfire cost regressions are available for the senior author). Our empirical model is:

Dependent Variable

Ln(TSC_i/$WFhectare_i$) = natural log of (Total Suppression $Costs_i$/Wildfire $Hectare_i$)

TSC_i **=** Total Suppression Costs of wildfire i

$WFhectare_i$ = size of wildfire i in hectares

Independent Explanatory Variables

Hectare_Mech = Hectares of the wildfire area with prior mechanical fuel treatment

Hectare_RXFire = Hectares of the wildfire area with prior prescribed fire fuel treatment

$WUIY_i$ =intercept shifter variable for whether the wildfire burned hectares in a WUI area

$Elev_i$ = average elevation of the wildfire area in meters

$Slope_i$ = average slope within the wildfire area

pls_i = percent of the area with low severity fire (less than 25% top kill). This variable is related to vegetation and disturbance dynamics in LANDFIRE (Ryan and Opperman, 2013).

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

(1) **ln(TSC_i/$WFhectare_i$)**

$$= B_0 - B_1(\mathbf{Hectare\_Mech}) - B_2(\mathbf{Hectare\_RXFire}) + B_3(\mathbf{WUIY_i}) + B_4(\mathbf{Elev_i}) + B_5(\mathbf{Slope_i}) - B_6(\mathbf{pls_i}) + \varepsilon_i$$

The coefficients on the fuel treatment variables should be negative and significant if the area of the fuel treatment reduces fire suppression costs. Mathematically our hypotheses are:

(2) Ho: $B_{HectareRXFire} = 0$ Ha: $B_{HectareRXFire} < 0$

(3) Ho: $B_{HectareMech} = 0$ Ha: $B_{HectareMech} < 0$

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

2.2 Property Damage Model

$$\textbf{(4)}\ \mathbf{ln(\#Structures_i)} = A_0 - A_1(\mathbf{lnWFhectare_i}) - A_2(\mathbf{Hectare\_Mech}) - A_3(\mathbf{Hectare\_RXFire}) + A_4(\mathbf{WUIY_i}) + A_5(\mathbf{Elev_i}) + A_6(\mathbf{Slope_i}) - A_7(\mathbf{pls_i}) + \varepsilon_i$$

Where #Structures is the sum of houses and other structures (barns, out buildings, unattached garages, etc.) damaged by wildfire_i. This equation was estimated with a count data model since there were a significant number of wildfires with no structures damaged and several wildfires with only a few structures damaged. A count data is well suited to handle small integers, including zeros better than OLS regression does.

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

(5) Ho: $A_{HectareRXFire} = 0$ Ha: $A_{HectareRXFire} < 0$

(6) Ho: $A_{HectareMech} = 0$ Ha: $A_{HectareMech} < 0$

The hypotheses are tested based on asymptotic t-statistics on the two types of pre-suppression fuel treatments: RX fire and mechanical fuel treatments.

3. Data

3.1 Study Sites

To make the study as comprehensive as possible, we collected data on hectares of fuel treatments and wildfire suppression costs in all U.S. National Forest regions of the continental U.S. (i.e., except Alaska and Hawaii). Ecologically, and in terms of their fire regimes, Alaska and Hawaii are very different from all regions in the continental U.S. As detailed in section 3.3 below, we partially accounted for geographic and ecological differences within the continental U.S. by relying on Geographic Area Coordination Centers (GACC) used in forest fire dispatch. However, ecological differences could have been accounted for using ecoregions such as done by Barnett et al. (2016) or even Bailey's ecoregions (1988).

3.2 Development of Database for Wildfire Suppression Costs and Fuel Treatments

Data on individual wildfire suppression cost, fire size, whether WUI was burned, and structures destroyed were from the USDA FS standardized form FS-5100-29 Wildland Fire Report. This data was obtained for years 2010 to 2014 for fires involving National Forest lands in the lower 48 states. Such wildfires include fires that burn on National Forests, burns on other lands the USDA FS has protection responsibility for, threatens to spread to National Forests, and "fire complexes or merged fires" that include National Forests (FIRESTAT, 2016). The data on the FS-5100-29 is filled out by Ranger District or Forest level personnel. The USDA FS emphasizes the importance of recording accurate data on this form since the data will also be used for future resource management analysis (FIRESTAT, 2016). Nonetheless, there is some variability in how data is recorded across the country and over the five years of our data. For example acres of fire burned in WUI is based on accepted regional definitions of WUI. This variability is expected and common in most government and private industry data[1].

[1] These sources of variability are common in other government statistics such as CDC's data on flu which relies upon reported diagnoses of thousands of doctors across the country or cause of death which relies upon judgements of hundreds of

Nonetheless we checked the accuracy of key variables used in this analysis such as number of structures and residences destroyed against other sources of data for the same time period to ensure the accuracy. However, there were more serious concerns regarding the accuracy of the reported cost of suppression for small fires as the quality standards for reporting costs on these small fires is not as rigorous as with larger fires. An effort was made to collaborate with the USDA FS scientists at the Rocky Mountain Research Station to obtain more accurate wildfire suppression cost data for large wildfires (fires greater than 121 hectares). Thus, we restrict our analysis to fires 121 hectare or larger. This is the same size level used by Yoder and Gebert (2012) and Hand et al. (2016). This more accurate cost of suppression data was obtained and merged into the other wildfire suppression data (USDA FS standardized form FS-5100-29 Wildland Fire Report) describing wildfires to create a master wildfire suppression database where the unit of analysis is the individual fire.

Data on prescribed burning and mechanical fuel treatments was acquired from the USDA FS FACTS (Forest Service Activity Tracking System) treatment area database. Using the FACTS manual and discussions with USDA FS fire specialists in northern California the individual FACTS treatment activities were classified into prescribed burning or mechanical fuel treatments (thinning, chipping, pruning, salvage cut). In larger fires there were some hectares that had both elements of mechanical treatment and prescribed burning treatments. In this case, a given hectare would be recorded in our regression data as having received both types of treatment. However, given the rarity of mechanical fuel treatment relative to prescribed burning, it was unusual to have a given hectare treated by both fuel reduction methods. The FACTS data was also checked for any anomalies in terms of "projections", meta-data and problems in latitude-longitude. Identified problems were resolved by contacting the USDA FS staff specialist responsible for this data.

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coroners across the country.

The vast majority of fuel treatments occurred in a relatively short time period prior to the time period of the wildfires we evaluated. We had spatially accurate fuel treatment data from 2007 to 2014. However, we only had a few hundred fuel treatments in 2007-2009, with about 1,300 in 2010. The vast majority (94%) of the fuel treatments (6,500 to 8,000 treatments per year) occurred in 2011-2014 time period. Of course, the hectares treated had to occur prior to the wildfire ignition date in order to be counted as a "hectare treated" in the analysis of a given wildfire. As such, most of the fuel treatments are likely only 2-3 years old at the time the wildfires occurred during the 2010 to 2014 time period. Thus, a 2014 year wildfire—the last year in our data—paired with a 2011 treatment would be just a three year lag. Nonetheless, we did not explicitly account for the lag effect of deterioration in the effectiveness of fuel treatments. This omission of lag effects could be important as Agee and Skinner (2005) document deterioration of prescribed fire fuel treatments in previously untreated stands in as little as four years (see Vaillant et al. (2009), Agee and Skinner (2005), and Finney et al. (2007) for an evaluation of this issue of decay of fuel treatment effectiveness). Thus, explicitly modeling lag effects is an important refinement in future research. Each hectare treated by each fuel treatment method were geolocated, and then overlain on the area of wildfire to calculate the number of hectares of the wildfire that were treated by each type of fuel treatment. This data was then merged into the wildfire suppression cost data along with GIS spatial data on the area of the treatments and wildfires (e.g., slope, elevation) to create the master dataset used for the regression analysis. The geographic area of the wildfires was calculated by using the longitude and latitude and the fire size.

3.3 Determining Geographic Regions of Analysis

Since we expect some geographic differences in how suppression costs respond to fuel treatments, we evaluated different options for grouping geographic areas. One choice was to use USDA FS Regions as that approach has been used before (Hand et al. 2016). However, while each of these large wildfires (300+ hectare) involved National Forests they sometimes included lands administered by the Bureau of Land Management (BLM), National Park Service (NPS), Bureau of Indian Affairs (BIA), as well as state lands and private lands. In these cases where multiple land ownerships are involved, the Geographic Area Coordination Centers (GACC) are used by the USDA FS for making fire suppression decisions, including logistics and dispatch. For GACCs with a large enough sample size of individual fires to provide sufficient degrees of freedom, we performed the analysis at the individual GACC level. However, for the Northeastern GACC there were not enough individual wildfires and structures damaged to run this region separately. Therefore, we combined it with the Southeastern GACC but we included a Southeastern dummy variable (GACCSoCC) to control for any geographic differences. We also pooled the Northern and Southern California GACCs into one fire suppression cost analysis area and included a dummy variable (GACCSoCA) for the Southern California GACC.

3.4 Selected Descriptive Statistics

Tables 1a and 1b provide the descriptive statistics for the variables used in the regressions (tables at end of paper). As can be seen by comparing the mean and median of the Hectare_RXFire and Hectare_Mech variables, less than half the wildfire areas have any fuel treatments. In terms of hectares of the wildfire area treated, prescribed fire was by far the dominant fuel treatment in wildfire areas (this is a similar pattern observed by Vaillant and Reinhardt (2017) which found that twice as many hectares of National Forests had been treated with prescribed burning than mechanical treatment from 2008-2012). Across most GACCs between 20%-30% of the fires involved WUI areas. In terms of the number of structures damaged, California had the most per fire, with the Rocky Mountains and Great Basin GACCs being the next highest.

Table 1a. Descriptive Statistics for East & South GACCs, Northern Rockies GACC and Rocky Mountain GACC. (See end of the paper)

Table 1b. Descriptive Statistics for Southwest GACC, Northwest GACC, Great Basin GACC and California GACCs. (See end of the paper)

4. Results

4.1 Statistical Results of Wildfire Suppression Cost

Tables 2a-2c presents the regression results for all seven geographic areas.

Table 2a. Suppression Cost Per Hectare Regression for Northeast & Southeast GACCs, Northern Rockies GACC and Rocky Mountain GACC. (See table at end of paper)

Table 2b. Suppression Cost Per Hectare Regression for Southwest, Pacific Northwest and Great Basin GACCs. (See table at end of paper)

Table 2c. Suppression Cost Per Hectare Regression for California GACCs. (See table at end of paper)

Most of the variable coefficient signs are as expected. Wildfires involving WUIY areas generally (five of the seven regions) result in higher suppression costs. This is the opposite result than Hand et al. (2016) although they measured this variable as housing value inside the fire perimeter and find it negative and significant. Greater slopes also result in higher suppression costs in four geographic regions, a result also different than Hand et al. (2016), although they used a series of dummies to measure slope. Elevation was significant in only one of our regions, but was significant in both of Hand et al. model specifications. In terms of our hypotheses tests, only in California do hectares of mechanical fuel treatment (Hectare_Mech) within the fire perimeter have a statistically significant effect of reducing wildfire suppression costs. The coefficient on prescribed fire (Hectare_RXFire) was never statistically significant across the seven geographic regions.

As noted above in our review of the theoretical literature, 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) points out, this result is theoretically expected to the extent that suppression and fuel treatments are complementary inputs in the wildland fire production process. In addition, as noted in our empirical literature review, Thompson and Anderson (2015) suggest there may simply be too few fuel treatments in areas with wildfires to detect any effects of fuel treatments on wildfire suppression costs. That lack of significance of prescribed burning (Hectare_RXFire) and mechanical fuel reduction (Hectare_Mech) almost uniformly across all but one GACC regions is consistent with the findings of Yoder and Ervin (2012). Our general lack of significance of fuel treatments in reducing wildfire suppression costs is also consistent with the more sophisticated propensity scoring model applied to fine scale geographic data in northeastern Florida by Butry (2009).

4.2 Results for Effect of Fuel Treatment of Property Damages

As was shown previously in Tables 1a and 1b, over half the fires do not damage any structures, and many of the fires only damage a small number of structures (e.g., houses, barns, and out buildings). This data structure suggests a count data model is a more appropriate statistical technique to estimate the effect of fuel treatments on the number of properties damaged than is OLS.

The results in Tables 3a-3c show that wildfires in WUI areas naturally resulted in more structures damaged. In terms of our hypothesis, in four GACCs the coefficient on prescribed fire is negative and statistically significant, indicating that as hectares treated with prescribed fire in a given wildfire went up, the number of structures damaged decreased (in two GACCs prescribed fire was not significant). The results were more mixed for mechanical fuel reduction. Only in two of the GACCs did the area of the wildfire treated with mechanical fuel reduction have a negative and statistically significant effect on reducing the number of structures damaged by fire. Thus, for some geographic areas, Rideout et al.'s (2008) interpretation that prescribed burning and mechanical fuel reduction may reduce property damages seems to apply.

Table 3a. Count data models for Structures damaged by wildfire Eastern & Southern GACCs, Northern Rockies GACC and Rocky Mountain GACC. (Table at end of paper)

Table 3b. Count data models for Structures damaged by wildfire Southwest GACC, Pacific Northwest GACC and Great Basin GACC. (Table at end of paper)

Table 3c. Count data models for Structures damaged by wildfire California GACCs. (Table at end of paper)

5. Conclusion

Across all National Forests in the continental U.S., we found that fuel treatments rarely had a significant effect on reducing wildfire suppression costs. This is consistent with the finding of Butry (2009) at the micro scale for northeastern Florida, and Yoder and Ervin (2012) for the western U.S. As noted in the literature review (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 or better prioritization of where fuel treatments occur (Barnett et al. 2016). Alternatively, as pointed out by Rideout et al. (2008), fuel treatments can increase the effectiveness of wildfire suppression efforts leading to reduced resource damage and property damages. In the case of property damages, Rideout et al. (2008) hypothesis seems at least partially borne out by our data. In particular, prescribed burning resulted in lower property damages from wildfires in four geographic regions. This may suggest emphasizing prescribed burning in WUI areas since 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 latest wildfire seasons are available, since fires in the last two years 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. We utilized fairly standard statistical techniques such as OLS regression and count data models, and not more sophisticated propensity scoring models suggested by Butry (2009). Perhaps propensity scoring models might have been able to better detect the effect of fuel treatments (although Butry's results using the propensity scoring method at a local scale in northeast Florida found similar results to ours in terms of the effect of fuel treatments). As noted in the data section, we focused on fires of 121 hectares 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. While other researchers have also relied upon this same 121 hectare plus wildfire data, it is possible that with data on a wider range of fire sizes (e.g., fires of 50 hectare and larger) that there may be more of an effect of pre-suppression fuel treatments in reducing fire suppression costs. Further, our current research results also suggest another related hypothesis. Specifically, that one potential effect of pre-suppression fuel treatments may be to keep small fires from growing into larger, more expensive to control fires. While we do not have data to test this hypothesis, the basic idea has been studied by Parks et al (2015). Specifically they found that prior wildfires (which they used as a proxy for fuel treatments) did limit the fire spread of subsequent wildfires, hence ultimately resulting in a smaller size of that new wildfire. Since they did not evaluate these consequences to wildfire suppression costs, this is an important avenue for future research if the quality of fire suppression cost data on small fires is improved in the future.

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Table 1a. Descriptive Statistics for East & South GACC's, Northern Rockies GACC and Rocky Mountain GACC

	East and SO		NRCC		RMCC	
Variable	Mean	Median	Mean	Median	Mean	Median
Ln (Supp Cost/WFHectare)	4.31	4.14	4.610	4.31	4.79	5.32
Hectare_Mech	0.03	0.00	0.006	0.00	0.05	0.00
Hectare_RXFire	55.20	0.00	73.680	0.00	61.97	0.00
WUIY	0.30		0.080		0.28	
Elevation (meters)	307.25	274.11	1680.400	1757.00	1907.00	2027.00
Slope	7.31	6.11	19.110	20.98	10.95	11.25
pls	17.22	17.38	4.417	2.80	7.24	5.44
#Structures Damaged/fire	0.38	0.00	0.460	0.00	1.75	0.00
Sample Size	174		142		81	

Table 1b. Descriptive Statistics for Southwest GACC, Northwest GACC, Great Basin GACC and California GACC's

	SWCC		NWCC		GBCC		CACC's	
Variable	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Ln (SuppCost/WFHectare)	4.73	4.74	5.75	6.29	5.92	5.85	6.73	6.94
Hectare_Mech	0.03	0.00	0.04	0.00	0.03	0.00	0.01	0.00
Hectare_RXFire	89.72	0.00	38.62	0.00	76.18	0.00	76.28	0.00
WUIY	0.18		0.19		0.19		0.32	
Elevation (meters)	1970.90	2044.40	1128.80	1757.00	2029.00	2027.00	1161.70	1058.20
Slope	11.81	11.83	18.10	20.98	17.23	11.25	17.43	17.77
pls	11.12	9.13	2.80	7.63	5.44	10.73	10.50	11.11
# Structures Damaged/fire	0.56	0.00	0.24	0.00	1.46	0.00	3.40	0.00
Sample Size	170		90		132		115	

Table 2a. Suppression Cost Per Hectare Regression for Northeast & Southeast GACCs, Northern Rockies GACC and Rocky Mountain GACC

	Group 1: GACCs Eastern and Southern		**Group 2: GACC Northern Rockies**		**Group 3: GACC Rocky Mountain**	
	Estimate	Probability	Estimate	Probability	Estimate	Probability
Intercept	3.0522	1.76e-07 ***	3.8557	2.28e-05 ***	2.4894	3.25e-05 ***
(t-statistic)	(5.454)		(4.389)		(4.426)	
GACCSoCC	0.5279	0.0641*				
	(1.864)					
Hectare_Mech	-0.1718	0.7951	4.3541	0.2136	0.5303	0.4277
	(-0.260)		(-1.250)		(0.798)	
Hectare_RXFire	-0.0004	0.3023	-0.0001	0.7610	-0.0005	0.3440
	(-1.035)		(-1.810)		(-0.952)	
WUIY	1.1712	7.76e-06 ***	2.8761	0.0002 ***	1.5817	0.0044 ***
	(4.617)		(3.806)		(2.939)	
Elevation	-0.0004	0.2241	0.0005	2.893	0.0004	0.3820
	(-1.220)		(1.064)		(0.880)	
Slope	0.0638	0.0017 ***	0.0012	0.9622	0.1023	0.0369 **
	(3.194)		(0.047)		(2.125)	
pls	0.0122	0.6542	-0.0651	0.1566	0.0120	0.6020
	(0.449)		(-1.464)		(0.524)	
R squared	**0.2024**		**0.1116**		**0.3800**	

*significant at the 10% level, ** significant at the 5% level and *** significant at the 1% level

Table 2b. Suppression Cost Per Hectare Regression for Southwest GACC, Pacific Northwest and Great Basin GACC

	Group 4 GACC Southwest		**Group 5: GACC Pacific Northwest**		**Group 6: GACC Great Basin**	
	Estimate	Probability	Estimate	Probability	Estimate	Probability
Intercept	2.1744	0.0015 **	4.800	1.09e-08 ***	5.988	6.51e-12 ***
(t-statistic)	(3.228)		(6.350)		(7.587)	
Hectare_Mech	0.4490	0.4693	4.649e-01	0.5910	2.023e-01	0.7685
	(0.725)		(0.540)		(-0.295)	
Hectare_RXFire	-0.0003	0.2674	-2.533e-05	0.9660	-6.473e-05	0.8581
	(-1.113)		(-0.043)		(-0.179)	
WUIY	0.4383	0.2410	-1.717e-01	0.7980	9.063e-01	0.0353**
	(1.177)		(-0.256)		(2.127)	
Elevation	0.0010	0.0064***	3.384e-04	0.4900	1.028e-05	0.9754
	(2.763)		(0.694)		(0.031)	
Slope	0.0646	0.0056***	4.523e-02	0.1130	-1.225e-02	0.5971
	(2.809)		(1.604)		(-0.530)	
pls	-0.0178	0.5514	-2.599e-02	0.2890	-6.183e-03	0.7803
	(-0.597)		(-1.068)		(-0.280)	
R-squared	**0.1181**		**0.0539**		**0.0445**	

*significant at the 10% level, ** significant at the 5% level and *** significant at the 1% level

Table 2c. Suppression Cost Per Hectare Regression for Southern and Northern California GACC

	Group 7: GACCs Southern & Northern CA	
	Estimate	Probability
Intercept	6.227e+00	1.69e-15 ***
(t-statistic)	(9.329)	
GACCSoCA	-2.614e-01	0.4116
	(-0.824)	
Hectare_Mech	-6.451e+00	0.0048***
	(-2.882)	
Hectare_RXFire	-1.053e-04	0.2220
	(-1.228)	
WUIY	-5.679e-01	5.21e-07 ***
	(-5.018)	
Elevation	-0.0005	0.1145
	(-1.591)	
Slope	3.992e-02	0.05764*
	(1.919)	
pls	2.704e-02	0.1725
	(1.373)	
R-squared	**0.1720**	

*significant at 10%; **significant at 5% level and ***significant at 1% level

Table 3a. Count data models for Structures damaged by wildfire Eastern & Southern GACCs, Northern Rockies GACC and Rocky Mountain GACC

	Group 1: GACCs Eastern and Southern		**Group 2: GACC Northern Rockies**		**Group 3: GACC Rocky Mountain**	
	Estimate	Probability	Estimate	Probability	Estimate	Probability
Intercept (t-statistics)	-9.1775 (-4.186)	2.84e-05 ***	-1.129e+01 (-8.540)	< 2e-16 ***	-1.491e+01 (-21.171)	<2e-16***
GACCSoCC	-4.6055 (-7.562)	3.97e-14 ***				
lnWFhectare	0.5181 (2.937)	0.00331***	1.183 (8.496)	< 2e-16 ***	1.579 (26.740)	<2e-16 ***
Hectare_Mech	-58.5281 (-0.990)	0.32228	-2.986 (-4.049)	5.14e-05 ***	-4.561e+01 (-2.313)	0.0207 *
Hectare_RXFire	0.0020 (5.515)	3.49e-08 ***	-5.435e-04 (-1.810)	0.0704*	-5.096e-03 (-13.828)	<2e-16***
WUIY	4.6003 (4.472)	7.76e-06 ***	3.321 (10.969)	< 2e-16 ***	3.838 (26.521)	<2e-16 ***
Elevation	0.0005 (0.506)	0.61320	1.480e-03 (4.212)	2.53e-05 ***	2.857e-04 (1.905)	0.0568*
Slope	-0.3360 (-2.617)	0.00887 **	-1.626e-01 (-6.324)	2.55e-10 ***	6.334e-02 (4.344)	1.46e-05***
pls	0.2400 (4.746)	2.07e-06 ***	-4.790e-03 (-0.116)	0.9079	-8.112e-02	0.003 ***
McFadden's R-squared	**0.7984**		**0.5679**		**0.8667**	

*significant at the 10% level, ** significant at the 5% level and *** significant at the 1% level

Table 3b. Count data models for Structures damaged by wildfire Southwest GACC, Pacific Northwest GACC and Great Basin GACC

	Group 4: GACC Southwest		**Group 5: GACC Northwest**		**Group 6: GACC Great Basin**	
	Estimate	Probability	Estimate	Probability	Estimate	Probability
Intercept	-2.434e+01	<2e-16 ***	-8.2249	4.87e-05 ***	-3.8016	< 2e-16 ***
(t-statistic)	(-14.881)		(-4.062)		(-9.712)	
lnWFhectare	1.184	<2e-16 ***	0.7736	1.47e-05 ***	0.5613	< 2e-16 ***
	(10.167)		(4.334)		(16.948)	
Hectare_Mech	5.561e-01	0.556	0.1315	0.7649	-3.6940	0.195
	(0.589)		(0.299)		(-1.296)	
Hectare_RXFire	-5.792e-05	0.487	-0.0002	0.6682	-0.0061	9.04e-05 ***
	(-0.695)		(-0.429)		(-3.915)	
WUIY	4.391	<2e-16 ***	1.7696	0.00054 ***	1.1464	< 2e-16 ***
	(11.619)		(3.460)		(9.924)	
Elevation	3.002e-03	<2e-16 ***	0.0007	0.3878	0.0002	0.212
	(11.774)		(0.864)		(1.249)	
Slope	2.148e-01	<2e-16 ***	0.0119	0.7023	-0.0505	4.63e-09 ***
	(9.415)		(0.382)		(-5.860)	
pls	-1.888e-02	0.734	-0.2456	0.9079	0.0101	0.217
	(-0.340)		(-2.979)		(1.233)	
McFadden's R-squared	**0.9109**			**0.4152**		**0.3185**

*significant at the 10% level, ** significant at the 5% level and *** significant at the 1% level

Table 3c. Count data models for Structures damaged by wildfire California GACCs

	Group 7: GACCs Southern & Northern CA	
	Estimate	Probability
Intercept	-6.6272	<2e-16 ***
(t-statistics)	(-14.523)	
GACCSoCA	1.6216	<2e-16 ***
	(10.126)	
lnWFhectare	1.0229	<2e-16**
	(22.51)	
Hectare_Mech	16.0169	<2e-16 ***
	(11.395)	
Hectare_RXFire	-0.0099	5.45e-05 ***
	(-4.035)	
WUIY	-0.6337	5.21e-07 ***
	(-5.018)	
Elevation	-0.0005	0.0116**
	(-2.524)	
Slope	0.0432	3.53e-06 ***
	(4.637)	
pls	-0.2559	< 2e-16 ***
	(-13.838)	
McFadden's R-squared	**0.5823**	

*significant at 10%; **significant at 5% level and ***significant at 1% level