Do Fuel Treatments in U.S. National Forests Reduce Wildfire Suppression Costs and Property Damage?

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Abstract | This article tests two hypotheses on whether forest 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 damage associated with wildfires in United States National Forests over a five-year period throughout the continental United States. The continental U.S. pooled data model results show that overall, prescribed burning reduces suppression cost and both fuel treatment types reduce property damages. Further analysis was done to separate the data into seven geographic regions of the United States. Results of the multiple regressions show that in California and the northern Rockies, mechanical fuel treatments reduce wildfire

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suppression costs, while only in California did prescribed burning reduce the cost. The second hypothesis tested is that fuel treatments, by making wildfires less damaging and easier to control, may reduce property damage. 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 effect in reducing property damage in two of the three regions.

Keywords | mechanical fuel reduction, prescribed burning, wildfires, wildland–urban interface

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 United States Department of Agriculture Forest Service (USDAFS) has incurred wildfire suppression costs of over $19 billion fighting wildfires that have burned more than 39 million hectares of forest and brush lands (National Interagency Fire Center [NIFC], 2016). In California, two of the most deadly and destructive wildfires occurred in 2017 and 2018. These suppression costs include personnel and equipment used specifically to contain the fire, protect lives and property, and usually extinguish a fire. Despite these efforts, in the period from 1999 to 2010, more than 1100 homes were burned and a total of 230 lives lost (Gude et al., 2013). Other statistics show that the number of fatalities due to wildland fires in the United States from 1910 to 2017 was 1128 (https://www.nifc.gov/safety/safety_documents/Fatalities-by-Year.pdf). The 2017 wildland fires in California demonstrate the significant socioeconomic impacts of wildland fires. Over 250 fires in northern California burned more than 245,000 acres, destroyed 8900 structures, and caused 44 deaths. More recently, the Camp Fire (Paradise, CA) become the most destructive and deadliest fire in California's history, destroying more than 18,800 structures and causing 85 deaths (Cal Fire, 2018b). In southern California, the second largest wildland fire in the state history burned 281,893 acres, destroyed 1063 structures, and caused 2 deaths (Cal Fire, 2018a). Additionally, there is growing recognition of the futility of fighting fires in ecosystems where prior fire suppression policies have led to buildup of dangerous forest fuels such as dense stands of trees and shrubs, dead and dying trees, and downed trees on the forest floor.

One strategy for reversing this trend is to perform what are referred to as fuel reduction treatments. This paper studies two such methods in depth: (a) Prescribed or controlled burning. This involves intentionally setting low-intensity fires (often in the spring when the forest is relatively wet) to reduce the amount of flammable material. (b) Mechanical fuel reduction. This method includes thinning the forest by selectively removing a fraction of the trees in a given stand of trees and "mowing" or grinding up shrubs or, in southern California, chaparral. 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 in U.S. national forests over the past five years. Specifically, we evaluate the effect of prescribed/controlled burning and mechanical fuel reduction treatments within the area burned by a wildfire in reducing (a) wildfire suppression costs and (b) 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. Our study is the first to do this analysis at the individual fire level for the entire continental U.S. national forests. In this respect, our study results should have greater generalizability or external validity than much of the prior literature, which has tested the effect of fuel treatments on wildfire suppression costs in just a few geographic areas.

Literature review

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 (where it 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 suppression cost and wildfire damages also depend on the agency's goals and constraints. Our case study uses data from the U.S. Forest Service on fires that involve national forests (either fires starting on these lands, or fires spreading to these lands from outside the national forests). One document explicitly providing a list of objectives is the U.S. Forest Service's Cohesive Strategy (U.S. Forest Service, 2000). This document provides goals similar to those of U.S. Department of the Interior agencies (National Park Service, Bureau of Land Management, and U.S. Fish and Wildlife Service). Specifically, these agencies have a hierarchy of saving human life first (including not putting firefighters' lives at risk), structures next, and protecting natural resources last (especially municipal watersheds and threatened and endangered species habitat; U.S. Forest Service, 2000). In addition, agencies often face capacity constraints, as there are only so many firefighters, fire engines, airplanes, and helicopters. Agencies have developed dispatch models to allocate these resources efficiently (Wei et al., 2015).

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 the size of wildfires in terms of burned acreage. Fewer articles address whether fuel treatments reduce suppression expenditures. We review all three types, as they all provide different insights into 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 chose the independent variables we did, and how our results compare with what others have found on topics most closely related to ours.

The empirical literature regarding the determinants of suppression costs suggests that a wide range of factors are at play. Suppression costs in an area increased with home values in the western United States (Gebert et al., 2007; Hand et al., 2016; Yoder and Gebert, 2012[1]) and the northern Rockies (Liang et al., 2008), the simple presence of homes in California's Sierra Nevada (Gude et al., 2013), and the spatial configuration of homes on the landscape in Colorado, Montana, and Wyoming (Scofield et al., 2015). Thus, fires in the WUI are a useful proxy for presence of homes in the area of a wildfire. In addition, Scofield et al. (2015) found not only that do homes in the WUI matter, but also that whether the homes are widely dispersed in that landscape (e.g., 35- acre parcel development common in Colorado) versus clustered together had a significant effect on wildfire suppression costs. In particular, Scofield et al. (2015, 3) found that clustering of homes in WUI areas substantially lowers firefighting costs relative to those for the same number of homes being widely dispersed throughout the landscape. Other important variables that influenced suppression costs in nearly all of the studies cited included biophysical variables such as elevation, slope, vegetation type, drought conditions, fuel moisture, wildfire intensity levels, and energy release component.

The literature most closely related to the purpose of our research includes papers by Butry (2009), Cochrane et al. (2012, Fitch et al. (2017)), Moghaddas and Craggs (2007), Parks et al. (2015), Thompson and Anderson (2015), Vaillant and Reinhardt (2017), and Yoder and Ervin (2012). Cochrane et al. (2012) investigated the effect of 1300 individual fuel treatments on 14 large wildfires using a simulation approach. They calibrated a simulation model for 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 wildfires acted as proxies 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, at least under moderate weather conditions, and thus likely reducing 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 (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 that "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" (Thompson and Anderson, 2015, 169). But Reinhardt et al. (2008) believe that the inability to know where the few large and expensive to suppress fires will occur suggests 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), Barnett et al. (2016) and Vaillant and Reinhardt (2017) 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) emphasize 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 for analyzing the effect of prescribed fire fuel treatment on suppression costs. Unfortunately, he does not compare the propensity scoring approach with OLS for his data, but he suggests that 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% significance level (another one is what he labels "weakly significant" at the 11% level). The extent to which these results are partially an artifact of relatively small fire size compared with that in other studies (including our own reported in this paper) is not known.

Moghaddas and Craggs (2007) studied the effect of a small one-year-old mechanical fuel treatment 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, which is about three times larger than our minimum fire size. Their wildfire suppression cost regression model includes as explanatory variables the dominant vegetation cover, wildfire size, and distance to WUI areas. Their dependent variable was the natural log 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. A 1% increase in the 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) directly test the effect of fuel treatments on fire suppression costs in the western United States. The authors ran 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, nor 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 for the biophysical variables of 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 has focused on fairly small geographic areas (e.g., one county or water district in Florida), which 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 are consistently available nationwide. Thus, not every variable that every paper has included can be included in our analysis. Therefore our analysis may have lower internal validity than more detailed studies on a small spatial scale. However, those studies have less generalizability or external validity. At the time we initiated this research, there had not been any individual-fire-level analyses of the effects of fuel reduction treatments on national forests nationwide. We felt that insights gained from the broader geographical generalizability (greater external validity) of these results would fill an important gap in the fuel treatment–wildfire suppression cost analysis literature.

Determinants of residences and structures destroyed by wildfire

Our second hypothesis test is that fuel reduction treatments, such as RX burning and mechanical fuel reduction, raise the marginal productivity of a given expenditure on 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 (the Wallow Fire) in the southwestern United States. 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 (barns, equipment sheds, etc.) destroyed by wildfires. Certainly one key element is the flammability of building materials used in the home (Cohen, 2000; Calkin et al., 2014). The land use configuration matters—also known as 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 in national forests, which surround many WUI communities throughout the United States. 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 the effectiveness of Firewise treatment is itself an important area of research, it is not the focus of our paper. For those interested in this topic we recommend Cohen (2010) and Evans et al. (2015).

Empirical model specification and hypothesis tests

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. For the wildfire suppression cost model, we use a standard OLS regression model, and for the structures damaged model, a Poisson count data model was used to account for the large number of zeros in the data. 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 the 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 methods and prescribed fire. Many other variables were initially identified and included in our preliminary model and were initially tested for best model fit using the backward stepwise regression procedure—selection based on the AIC. These variables include crown bulk density, fire intensity level, percent mixed-severity fires, and fire return interval. Acres of the wildfire in Wilderness was zero in three of our geographic regions used in the overall analysis. Therefore the Wilderness variable was not included in the regressions in these three regions. We did not collect data on fire duration, which is an omission that may reduce the overall explanatory power of our regressions. Ideal fire suppression cost models would also incorporate weather during the fire. We did not pursue obtaining those 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 important variables for future research to test, as the fires in California during the fall of 2017 suggest that 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 the total size of the wildfire. While we initially tried this specification, we chose the natural log of the suppression cost per hectare based on the data distribution. Figure 1 shows a skewed distribution, and after natural log transformation (Figure 2), the data are more normally distributed. In addition, the transformation may help to deal with any potential for heteroscedasticity across fires of quite different sizes, which might have been a problem had we used total suppression cost (using total suppression cost along with total wildfire size as a RHS variable gave us a much higher R^2, 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 basic empirical model is

$$\begin{aligned} &\ln(\mathrm{TSC}_i/\mathrm{WFhectare}_i) \\ &= B_0 - B_1(\mathrm{Hectare\_Mech}) - B_2(\mathrm{Hectare\_RXFire}) + \\ &B_3(\mathrm{WUIY}_i) + B_4(\mathrm{Elev}_i) + B_5(\mathrm{Slope}_i) - B_6(\mathrm{pls}_i) + \varepsilon_i \end{aligned} \tag{1}$$

$\mathrm{Ln}(\mathrm{TSC}_i/\mathrm{WFhectare}_i)$ = natural log of (Total Suppression Costs_i/Wildfire $\mathrm{Hectare}_i$),

where TSC_i is Total Suppression Costs of wildfire *i*, and $\mathrm{WFhectare}_i$ is the size of wildfire *i* in hectares. Independent explanatory variables are as follows: 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 = percentage 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).

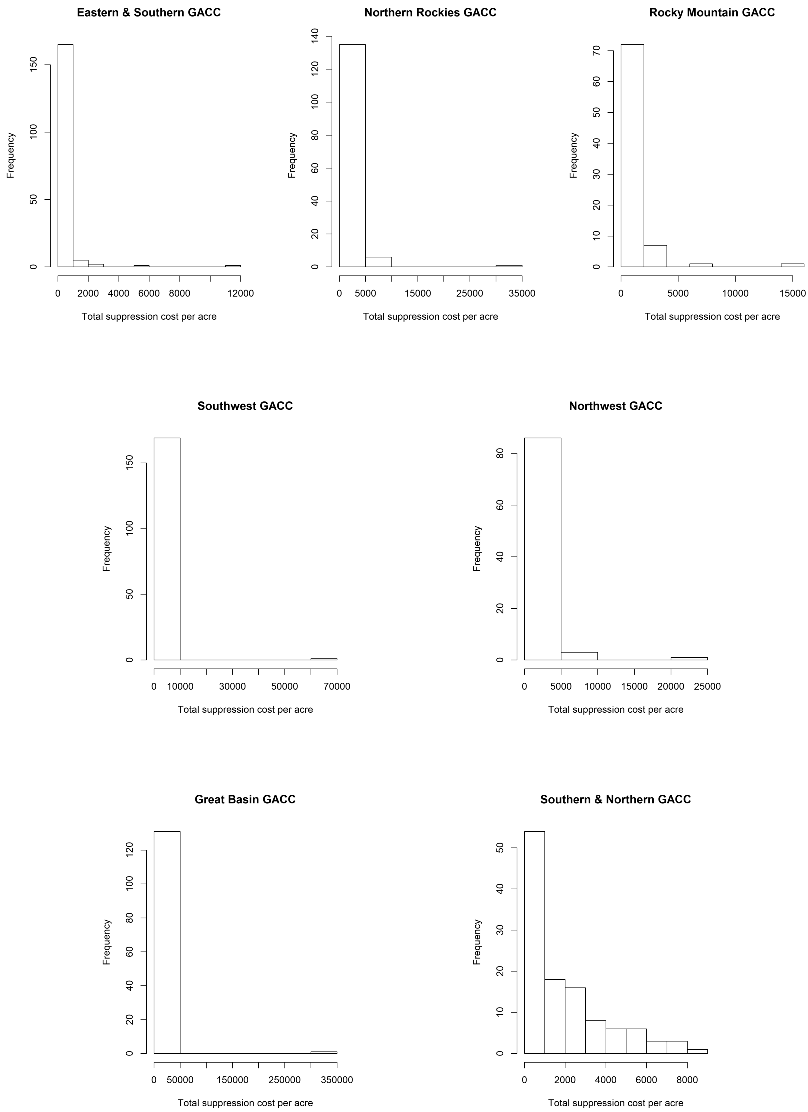

FIGURE 1 Histogram of total suppression cost per acre for each GACC.

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

$$\text{Ho: } B_{\text{HectareRXFire}} = 0 \qquad \text{Ha: } B_{\text{HectareRXFire}} < 0 \tag{2}$$

$$\text{Ho: } B_{\text{HectareMech}} = 0 \qquad \text{Ha: } B_{\text{HectareMech}} < 0 \tag{3}$$

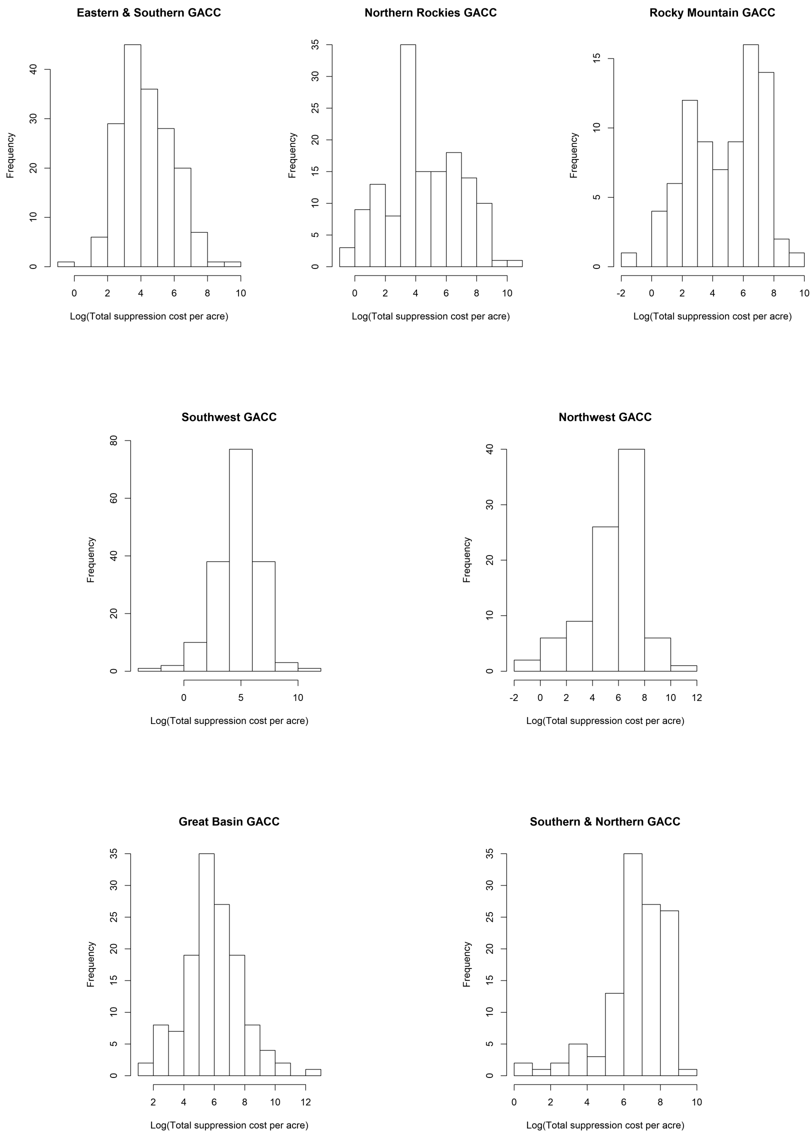

FIGURE 2 Histogram of natural log of total suppression cost per acre for each GACC.

The hypotheses are tested based on a coefficient's asymptotic individual t-statistics on the two types of presuppression fuel treatments. However, as suggested by a reviewer, we also provide a joint test of Hectare_Mech, Hectare_RXFire, and pls.

Property damage model

The model is

$$\ln(\#Structures_i) = A_o - A_1(\ln WFhectare_i) - A_2(Hectare\_Mech) - A_3(Hectare\_RXFire) + A_4(WUIY_i) + A_5(Elev_i) + A_6(Slope_i) - A_7(pls_i) + \varepsilon_i, \quad (4)$$

where: #Structures is the sum of houses and other structures (barns, outbuildings, unattached garages, etc.) damaged by $wildfire_i$ and all other variables are as defined in Equation (1).

This equation was estimated with a Poisson count data model, since there were a significant number of wildfires with no structures damaged and several wildfires with only a few structures damaged (see Figure 3 for data distribution). A Poisson count data model is well suited to handle small integers, including zeros, better than OLS regression does.

The hypotheses tests for property damage (# structures) are

$$\text{Ho: } A_{\text{HectareRXFire}} = 0 \qquad \text{Ha: } A_{\text{HectareRXFire}} < 0 \quad (5)$$
$$\text{Ho: } A_{\text{HectareMech}} = 0 \qquad \text{Ha: } A_{\text{HectareMech}} < 0 \quad (6)$$

The hypotheses are tested based on asymptotic *t*-statistics on the two types of presuppression fuel treatments: RX burning and mechanical fuel treatments.

Data

Study sites

To make the study as comprehensive as possible, we collected data on hectares of fuel treatment and wildfire suppression costs in all U.S. national forest regions of the continental United States (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 United States. As detailed in the next section, we partially accounted for geographic and ecological differences within the continental United States by relying on Geographic Area Coordination Centers (GACC) used in forest fire dispatch. However, ecological differences could have been accounted for using ecoregions as done by Barnett et al. (2016) or even Bailey's ecoregions (1988).

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 USDAFS standardized form

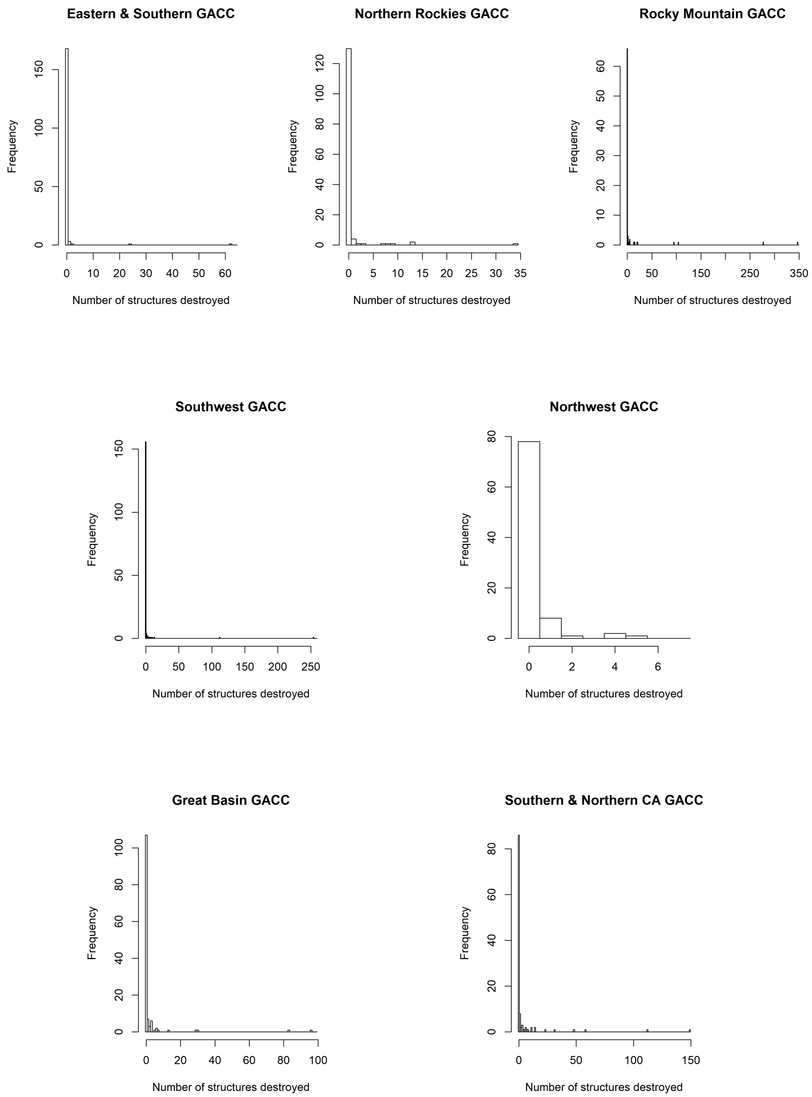

FIGURE 3 Histogram of number of structures destroyed by wildfires by GACC.

FS-5100-29 Wildland Fire Report. These data were obtained for the years 2010–2014 for fires involving national forest lands in the lower 48 states. Such wildfires include fires that burn in national forests, burn on other lands the USDAFS has protection responsibility for, or threaten to spread to national forests, and "fire complexes or merged fires" that include national forests (FIRESTAT, 2016). The data on the FS-5100-29 are filled out by ranger district or forest level personnel. The USDAFS 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 are recorded across the country and over the five years of our data. For example, acres of fire burned in WUI are based on accepted regional definitions of WUI. This variability is expected and common in most government and private industry data.[2] 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 accuracy.[3]

The dependent variable in this analysis is wildfire suppression costs. Originally we had intended to use wildfire suppression costs of all wildfires in national forests. However, we were repeatedly told that there were 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 are not as rigorous as with larger fires. Therefore, an effort was made to collaborate with the USDAFS 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 hectares or larger. This is the same size level used by Yoder and Gebert (2012) and Hand et al. (2016). Thus our analysis (like those of several others) is conditional on fire size being at least 121 hectares. We are therefore empirically testing whether the acres of prescribed burning and mechanical fuel reduction reduce the cost of suppressing fires that are at least 121 hectares or larger. If acres of fuel treatment reduce the suppression of medium to large fires, this is a very policy-relevant analysis, as it is the larger fires that are responsible for the vast majority of firefighting costs in the USDAFS. However, in the *Conclusions*, we discuss how this analysis can be improved upon once the USDAFS collects accurate fire cost data on small fires.

The more accurate cost-of-suppression data on large fires were obtained and merged into the other wildfire suppression data (USDAFS 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 RX burning and mechanical fuel treatments were acquired from the USDAFS FACTS (Forest Service Activity Tracking System) treatment area database. Using the FACTS manual and discussions with USDAFS 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 elements of both 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 were also checked for any anomalies in terms of "projections," metadata, and problems in latitude–longitude. Identified problems were resolved by contacting the USDAFS staff specialist responsible for the data.

The original fuels treatment dataset from the USDAFS indicated that 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 1300 in 2010. The vast majority (94%) of the fuel treatments (6500 to 8000 treatments per year) occurred in 2011–2014. Of course, the hectares treated had to occur prior to the wildfire ignition date to be counted as "hectares treated" in the analysis of a given wildfire. As such, most of the fuel treatments were likely only 2–3 years old at the time the wildfires occurred during the 2010–2014 time period. Thus, a 2014 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 Agee and Skinner, 2005, Finney et al., 2007, and Vaillant et al., 2009 for an evaluation of this issue of decay of fuel treatment effectiveness). Based on a reviewer's concern about the potential importance of lags, we investigated whether we could incorporate lags into our regression models. Unfortunately, the year of the fuel treatment variable did not get carried forward into the final geospatial datasets that merged fuel treatments, fire perimeters, and properties destroyed. At this point, we no longer have the budget to undertake the lengthy effort to reconstruct the dataset from scratch. Thus, explicitly modeling lag effects is an important refinement in future research. Each hectare treated by each fuel treatment method was geolocated, and then overlaid on the area of wildfire to calculate the number of hectares of wildfire that were treated by each type of fuel treatment. These data were 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 using the longitude and latitude and the fire size.

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 USDAFS regions as that approach has been used before (Hand et al., 2016). However, while each of these large wildfires (121+ hectares) involved national forests, they sometimes included lands administered by the Bureau of Land Management (BLM), National Park Service (NPS), or Bureau of Indian Affairs (BIA), as well as state lands and private lands. In cases where multiple land ownerships are involved, the GACC are used by the USDAFS 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 (hereafter East), there were not enough individual wildfires and structures damaged to run this region separately. Therefore, we combined it with the Southeastern GACC (labelled SO in Table 1, and Southern in the remaining tables), 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. The Northern Rockies GACC is labelled NRCC in Table 1a and the Rocky Mountain GACC is labelled RMCC in Table 1a. In Table 1b the Southwest GACC is labelled SWCC in Table 1b, the Pacific Northwest GACC is labelled NWCC, and the Great Basin GACC is labelled GBCC in Table 1b.

Selected descriptive statistics

Tables 1a and 1b provide the descriptive statistics for the variables used in the regressions. As can be seen by comparing the mean and median of the

TABLE 1A Descriptive statistics for East and SO GACC, NRCC GACC, and RMCC 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	73.68	0.00	61.97	0.00
WUIY	0.30	0.00	0.080	0.00	0.28	0.00
Elevation (m)	307.25	274.11	1680.40	1757.00	1907.00	2027.00
Slope	7.31	6.11	19.11	20.98	10.95	11.25
pls	17.22	17.38	4.417	2.80	7.24	5.44
#Structure 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 GACCs.

	SWCC		*NWCC*		*GBCC*		*CACC's*	
Variable	*Mean*	*Median*	*Mean*	*Median*	*Mean*	*Median*	*Mean*	*Median*
Ln(Supp Cost/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	0.00	0.19	0.00	0.19		0.32	
Elevation (m)	1971.90	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
#Structure damaged/fire	0.56	0.00	0.24	0.00	1.46	0.00	3.40	0.00
Sample size	170		90		132		115	

Hectare_RXFire and Hectare_Mech variables (see Figures 4 and 5 for data distribution), less than half the wildfire areas have any fuel treatments. In terms of hectares of wildfire area treated, prescribed fire was by far the dominant fuel treatment in wildfire areas (a similar pattern was observed by Vaillant and Reinhardt, 2017, who found that twice as many hectares of national forests had

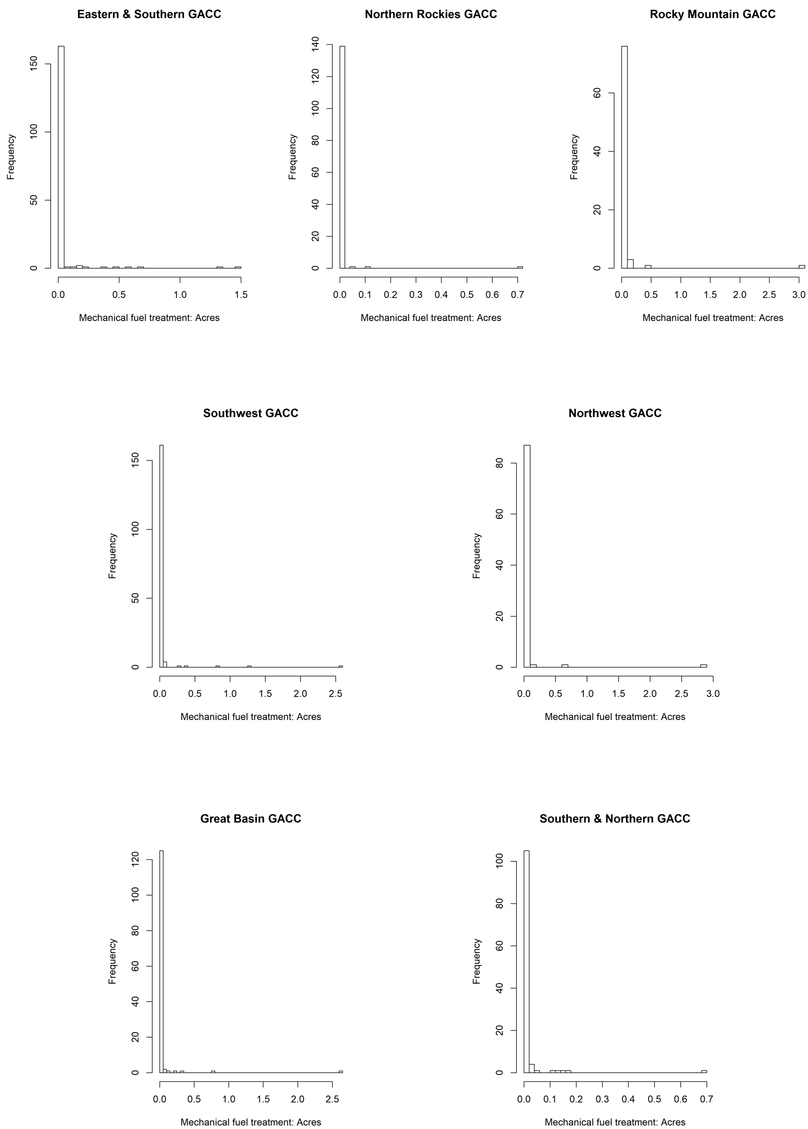

FIGURE 4 Histogram of mechanical fuel treatment by GACC.

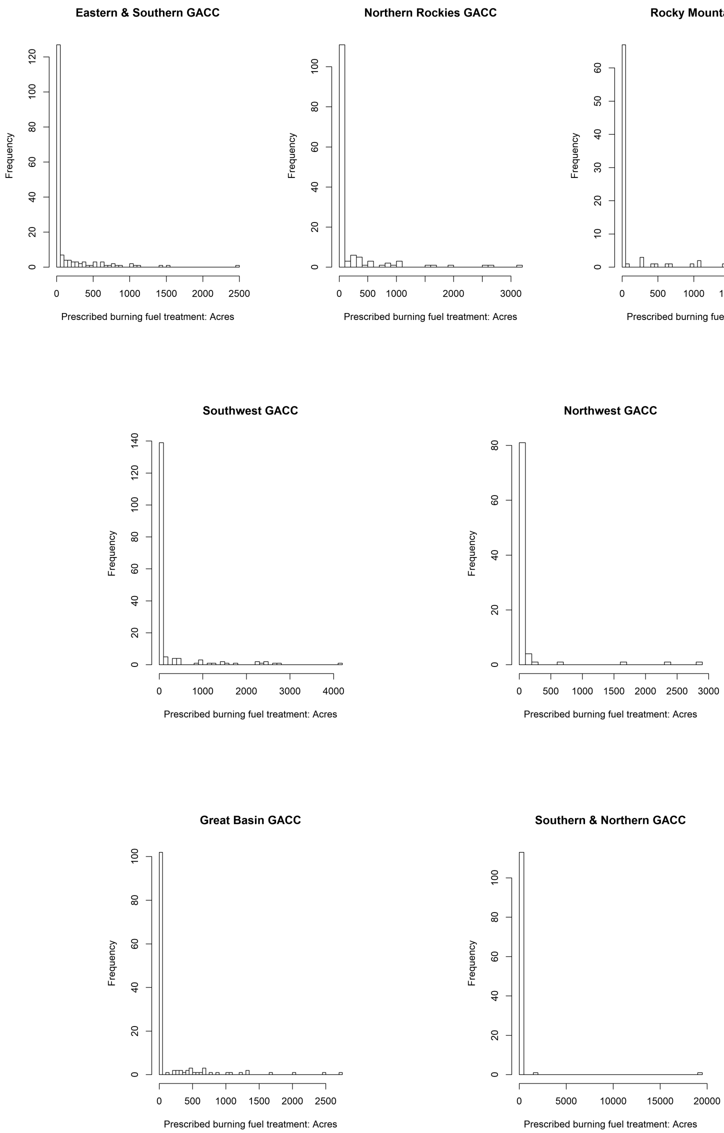

FIGURE 5 Histogram of prescribed burned fuel treatment by GACC.

been treated with RX burning as with mechanical treatment from 2008 to 2012). Across most GACCs, between 20 and 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.

Results

Statistical results for wildfire suppression cost

We used R statistical software for the data analysis (R Core Team, 2016). As suggested by a reviewer, our first regression and count data models pooled the data across all seven GACCs, but included GACC group intercept dummy variables. Due to the possibility of heteroscedasticity, the suppression cost model uses the White Huber robust standard errors, instead of traditional standard errors. The pooled data results show that overall, prescribed burning helps reduce suppression cost (Table 2a), and both fuel treatment variables help reduce property

TABLE 2A Suppression cost per hectare regression for all GACCs.

Variable	*Estimate*	*p-value*
Intercept	5.3135	$<2.2\times10^{-16}$***
(*t*-Statistic)	(18.0941)	
GACCESCC	−1.6854	1.383×10^{-10}***
	(−6.4177)	
GACCGBCC	−1.0966	3.962×10^{-05}***
	(−4.1097)	
GACCNRCC	−2.1963	1.138×10^{-15}***
	(−8.0110)	
GACCNWCC	−0.8886	0.0024***
	(−3.03733)	
GACCRMCC	−2.0437	1.406×10^{-11}***
	(−6.7573)	
GACCSWCC	−2.0680	$<2.2\times10^{-16}$***
	(−8.2114)	
Hectare_Mech	0.2646	0.0992*
	(1.6489)	
Hectare_RXFire	-1.4687×10^{-04}	0.0103**
	(−2.5669)	
WUIY	0.8859	1.695×10^{-08}***
	(5.6406)	
Elevation	4.7089×10^{-04}	0.0007***
	(3.3867)	
Slope	3.3680×10^{-02}	0.0003***
	(3.6108)	
pls	1.9312×10^{-03}	0.8261
	(0.2198)	
R^2	0.1987	

*Significant at the 10% level; ** significant at the 5% level; ***significant at the 1% level.

TABLE 2B Suppression cost per hectare regression for Northeast and Southeast GACCs, Northern Rockies GACC, and Rocky Mountain GACC.

	Group 1: GACC Eastern and Southern		*Group 2: GACC Northern Rockies*		*Group 3: GACC Rocky Mountain*	
Variable	*Estimate*	*p-value*	*Estimate*	*p-value*	*Estimate*	*p-value*
Intercept	3.0522	2.265×10^{-11}***	3.8557	1.42×10^{-07}***	2.4894	8.396×10^{-06}***
(*t*-statistic)	(6.6878)		(5.2627)		(4.4548)	
GACCSoCC	0.5279	0.0228**	–		–	
	(2.2763)					
Hectare_Mech	−0.1718	0.6579	−4.3541	0.0003***	0.5303	0.0133**
	(−0.4427)		(−3.6380)		(2.4750)	
Hectare_RXFire	−0.0004	0.2192	−0.0001	0.6992	−0.0005	0.2308
	(−1.2286)		(−0.3864)		(−1.1984)	
WUIY	1.1712	1.131×10^{-05}***	2.8761	2.969×10^{-07}***	1.5817	0.0022***
	(4.3905)		(5.1254)		(3.0683)	
Elevation	−0.0004	0.0333**	0.0005	0.2828	0.0004	0.4311
	(−2.1286)		(1.074)		(0.7873)	
Slope	0.0638	0.0021***	0.0012	0.9616	0.1023	0.0617*
	(3.0749)		(0.0481)		(1.8687)	
pls	0.0122	0.5977	−0.0651	0.1098	0.0120	0.3489
	(0.5277)		(−1.5992)		(0.9367)	
R^2	0.2024		0.1116		0.3800	

* Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level

TABLE 2C Suppression cost per hectare regression for Southwest GACC, Pacific Northwest GACC, and Great Basin GACC.

	Group 4: GACC Southwest		*Group 5: GACC Pacific Northwest*		*Group 6: GACC Great Basin*	
Variable	*Estimate*	*p-value*	*Estimate*	*p-value*	*Estimate*	*p-value*
Intercept	2.1744	0.0102**	4.800	1.601×10^{-05}***	5.988	3.61×10^{-14}***
(t-statistic)	(2.5690)		(4.3143)		(7.5743)	
Hectare_Mech	0.4490	0.1001	4.649×10^{-01}	0.0510*	2.023×10^{-01}	0.1833
	(1.6446)		(1.9512)		(1.3307)	
Hectare_RXFire	−0.0003	0.2807	-2.533×10^{-05}	0.9188	-6.473×10^{-05}	0.8670
	(−1.0788)		(-0.1019)		(-0.1675)	
WUIY	0.4383	0.2484	-1.717×10^{-01}	0.7668	9.063×10^{-01}	0.0143**
	(1.1542)		(-0.2965)		(2.4504)	
Elevation	0.0010	0.0076***	3.384×10^{-04}	0.5530	1.028×10^{-05}	0.9719
	(2.667)		(0.5933)		(0.0352)	
Slope	0.0646	0.0234**	4.523×10^{-02}	0.1366	-1.225×10^{-02}	0.5720
	(2.2673)		(1.4887)		(-0.5652)	
pls	−0.0178	0.5325	-2.599×10^{-02}	0.1699	-6.183×10^{-03}	0.7442
	(−0.6242)		(−1.3725)		(-0.3263)	
R^2	0.1181		0.0539		0.0445	

* Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

TABLE 2D Suppression cost per hectare regression for Southern and Northern California GACC.

	Group 7: GACCs Southern and Northern CA	
Variable	*Estimate*	*p-value*
Intercept (t-statistic)	6.227 (11.1289)	$<2.2\times10^{-16}$***
GACCSoCA	-2.614×10^{-01} (-0.9578)	0.3382
Hectare_Mech	-6.451 (-6.0548)	1.406×10^{-09}***
Hectare_RXFire	-1.053×10^{-04} (-5.0877)	3.624×10^{-07}***
WUIY	-5.679×10^{-01} (-1.5675)	0.1170
Elevation	-0.0005 (-0.1328)	0.8944
Slope	3.992×10^{-02} (2.2634)	0.0236**
pls	2.704×10^{-02} (1.2815)	0.2000
R^2	0.1720	

**Significant at the 5% level; ***significant at the 1% level.

damage (Table 3a). We tested for homogeneity for the regions as we expect differences by geographic regions. Based on Levene's test of homogeneity of variance, the null hypothesis is rejected, implying there is evidence to suggest that the variance of suppression cost and properties damaged are different between GACCs. Therefore, the data was also separated into GACCs (as mention above) for further analysis.

These individual GACC regression models were also estimated by OLS and using White Huber robust standard errors. Most of the variable coefficient signs (Tables 2b–2d) are as expected. Wildfires involving WUIY areas generally (five of the seven regions) result in higher suppression costs. This is the opposite result from Hand et al. (2016), although they measured this variable as housing value inside the fire perimeter and found it negative and significant. Greater slopes also result in higher suppression costs in four geographic regions, a result also different from Hand et al. (2016), although they used a series of dummies to measure slope. Elevation was significant in only two of our regions, but was significant in both of Hand et al. (2016)'s model specifications. In terms of our hypothesis tests, only in California and Northern Rockies do hectares of

TABLE 3A Poisson count data models for structures damaged by wildfire, all GACCs.

Variable	*Estimate*	*p-value*
Intercept	−7.301	$<2.2\times10^{-16***}$
(*t*-statistic)	(−42.383)	
GACCESCC	0.2867	0.0456**
	(2.00)	
GACCGBCC	−0.6595	$6.09\times10^{-14***}$
	(−7.506)	
GACCNRCC	−0.5174	$4.23\times10^{-05***}$
	(−4.095)	
GACCNWCC	−2.125	$<2\times10^{-16***}$
	(−9.887)	
GACCRMCC	1.071	$<2\times10^{-16***}$
	(12.115)	
GACCSWCC	−0.2101	0.0135**
	(−2.472)	
lnWFhectare	0.8046	$<2\times10^{-16***}$
	(54.377)	
Hectare_Mech	−1.051	0.0062***
	(−2.74)	
Hectare_RXFire	-3.534×10^{-04}	$<2\times10^{-16***}$
	(−9.936)	
WUIY	2.095	$<2\times10^{-16***}$
	(40.564)	
Elevation	2.783×10^{-04}	$5.8\times10^{-10***}$
	(6.196)	
Slope	1.542×10^{-02}	0.0003***
	(3.607)	
pls	-4.452×10^{-02}	$1.85\times10^{-14***}$
	(−7.66)	
McFadden's R^2	0.5639	

** Significant at the 5% level; ***significant at the 1% level.

mechanical fuel treatment (Hectare_Mech) within the fire perimeter have a statistically significant effect of reducing wildfire suppression costs. In two other GACC's (Rocky Mountain and Pacific Northwest), Hectare_Mech increased wildfire suppression costs. For these two geographic regions, Rideout et al.'s (2008) hypothesis test is supported; that is, more suppression effort occurred. The coefficients on prescribed fire (Hectare_RXFire) are all negative, but only in California are they statistically significant, implying that RX fire helps reduce suppression cost. As suggested by a reviewer, we performed a joint test of Hectare_Mech, Hectare_RXFire, and pls to check on the robustness of our

TABLE 3B Poisson count data models for structures damaged by wildfire, Eastern and 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*	
Variable	*Estimate*	*p-value*	*Estimate*	*p-value*	*Estimate*	*p-value*
Intercept (t-Statistic)	−9.1775 (−4.186)	2.84×10^{-05}***	$-1.129\times10^{+01}$ (−8.540)	$< 2\times10^{-16}$***	$-1.491\times10^{+01}$ (−21.171)	$<2\times10^{-16}$***
GACCSoCC	−4.6055 (−7.562)	3.97×10^{-14}***	–		–	
lnWFhectare	0.5181 (2.937)	0.00331***	1.183 (8.496)	$< 2\times10^{-16}$***	1.579 (26.740)	$<2\times10^{-16}$***
Hectare_Mech	−58.5281 (−0.990)	0.32228	−2.986 (−4.049)	5.14×10^{-05}***	$-4.561\times10^{+01}$ (−2.313)	0.0207**
Hectare_RXFire	0.0020 (5.515)	3.49×10^{-08}***	-5.435×10^{-04} (−1.810)	0.0704*	-5.096×10^{-03} (−13.828)	$<2\times10^{-16}$***
WUIY	4.6003 (4.472)	7.76×10^{-06}***	3.321 (10.969)	$< 2\times10^{-16}$***	3.838 (26.521)	$<2\times10^{-16}$***
Elevation	0.0005 (0.506)	0.61320	1.480×10^{-03} (4.212)	2.53×10^{-05}***	2.857×10^{-04} (1.905)	0.0568*
Slope	−0.3360 (−2.617)	0.00887***	-1.626×10^{-01} (-6.324)	2.55×10^{-10}***	-6.334×10^{-02} (4.344)	1.46×10^{-15}***
pls	0.2400 (4.746)	2.07×10^{-06}***	-4.790×10^{-03} (−0.116)	0.9079	8.112×10^{-02}	0.003***
McFadden's R^2	0.7984		0.5679		0.8667	

*Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

TABLE 3C Poisson 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*	
Variable	*Estimate*	*p-value*	*Estimate*	*p-value*	*Estimate*	*p-value*
Intercept (t-statistic)	$-2.434\times10^{+01}$ (−14.881)	$<2\times10^{-16}$***	−8.2249 (−4.062)	4.87×10^{-05}***	−3.8016 (−9.712)	$< 2\times10^{-16}$***
ln(WFhectare)	1.184 (10.167)	$<2\times10^{-16}$***	0.7736 (4.334)	1.47×10^{-05}***	0.5613 (16.948)	$< 2\times10^{-16}$***
Hectare_Mech	5.561×10^{-01} (0.589)	0.556	0.1315 (0.299)	0.7649	−3.6940 (−1.296)	0.195
Hectare_RXFire	-5.792×10^{-05} (−0.695)	0.487	−0.0002 (−0.429)	0.6682	−0.0061 (−3.915)	9.04×10^{-05}***
WUIY	4.391 (11.619)	$<2\times10^{-16}$***	1.7696 (3.460)	0.00054***	1.1464 (9.924)	$< 2\times10^{-16}$***
Elevation	3.002×10^{-03} (11.774)	$<2\times10^{-16}$***	0.0007 (0.864)	0.3878	0.0002 (1.249)	0.212
Slope	2.148×10^{-01} (9.415)	$<2\times10^{-16}$***	0.0119 (0.382)	0.7023	−0.0505 (−5.860)	4.63×10^{-09}***
pls	-1.888×10^{-02} (−0.340)	0.734	−0.2456 (−2.979)	0.9079	0.0101 (1.233)	0.217
McFadden's R^2	0.9109		0.4152		0.3185	

*** Significant at the 1% level.

TABLE 3D Poisson count data models for structures damaged by wildfire, California GACCs.

	Group 7: GACCs Southern and Northern CA	
Variable	*Estimate*	*p-value*
Intercept	−6.6272	$<2\times10^{-16***}$
(t-Statistic)	(−14.523)	
GACCSoCA	1.6216	$<2\times10^{-16***}$
	(10.126)	
lnWFhectare	1.0229	$<2\times10^{-16**}$
	(22.51)	
Hectare_Mech	16.0169	$<2\times10^{-16***}$
	(11.395)	
Hectare_RXFire	−0.0099	$5.45\times10^{-05***}$
	(−4.035)	
WUIY	−0.6337	$5.21\times10^{-07***}$
	(−5.018)	
Elevation	−0.0005	0.0116**
	(−2.524)	
Slope	0.0432	$3.53\times10^{-06***}$
	(4.637)	
pls	−0.2559	$< 2\times10^{-16***}$
	(−13.838)	
McFadden's R^2	0.5823	

**Significant at the 5% level; ***significant at the 1% level.

conclusions regarding statistical significance using *t*-tests on the individual fuel treatment coefficients. The results indicates we can't reject the null hypothesis that these three coefficients are zero for six of the seven groups. Specifically, for East/South GACC Group 1 $p = 0.7336$; NRCC GACC Group 2 $p = 0.2646$; RMCC GACC Group 3 $p = 0.5143$; SWCC GACC Group 4 $p = 0.5257$; NWCC GACC Group 5 $p = 0.6893$; GBCC GACC Group 6 $p = 0.9793$; CACC GACC Group 7 $p = 0.0089$. As can be seen, only in the case of the CACC did we reject the null hypothesis that the three coefficients are zero. The full econometric results can be requested from the senior author.

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 firefighters to enter areas that would otherwise not be safe, thereby raising wildfire suppression costs. As Rideout et al. (2008) point 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 that 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 RX burning (Hectare_RXFire) and mechanical fuel reduction (Hectare_Mech) almost uniformly across all but two 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).

Results for effect of fuel treatment on 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 outbuildings). This data structure suggests that a Poisson 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–3d show that wildfires in WUI areas naturally resulted in more structures damaged. In terms of our hypothesis, for the pooled data analysis, both prescribed fire and mechanical thinning are statistically significant, but only RX fire has the correct sign. For the individual group analysis, 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) hypothesis that prescribed burning and mechanical fuel reduction may reduce property damage seems to be supported.

Conclusions

The continental United States pooled data model results show that overall, prescribed burning reduces suppression cost and both fuel treatment types reduce property damages. In the more statistically defensible geographically disaggregated models, we found that fuel treatments rarely had a significant effect on reducing wildfire suppression costs. This is consistent with the findings of Butry (2009) at the micro scale for northeastern Florida, and Yoder and Ervin (2012) for the western United States. 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 of RX 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 damage. In the case of property damage, Rideout et al. (2008)'s hypothesis seems at least partially borne out by our data. In particular, RX burning resulted in lower property damage from wildfires in four geographic regions. This may suggest emphasizing RX burning in WUI areas, since the primary benefits of such fuel reduction projects is in reducing property damage rather than reducing wildfire suppression costs. But this evidence should be revisited after data on the 2017 and 2018 wildfire seasons are available, since fires that year 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 with robust standard errors and Poisson 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 results similar 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 that fire suppression cost data on smaller fires were not reliable. While other researchers have also relied upon these same 121-hectare-plus wildfire data, it is possible that with data on a wider range of fire sizes (e.g., fires of 50 hectares and larger) there may be more of an effect of presuppression fuel treatments in reducing fire suppression costs. Further, our current research results also suggest another related 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. 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, ultimately resulting in a smaller size of those new wildfires. Since they did not evaluate these consequences of 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.

Notes

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1. Yoder and Gebert (2012) and Hand et al. (2016) developed an econometric model to determine which of several variables influence wildfire suppression cost. These models use the same source of USDAFS data as we do in terms of fires 300 acres (121 hectares) or larger. However, they were not testing for whether fuel treatments reduce wildfire suppression costs.

2. These sources of variability are common in other government statistics, such as CDC's data on flu, which rely upon reported diagnoses of thousands of doctors across the country, or cause of death, which rely upon judgments of hundreds of coroners across the country.

3. For example, we compared annual reports of the total number of structures burned each year with the sum of number of structures burned in all our geographic regions each year to make sure these numbers matched.

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