Estimating Suppression Expenditures for Individual Large Wildland Fires

Krista M. Gebert, David E. Calkin, and Jonathan Yoder

ABSTRACT

The extreme cost of fighting wildland fires has brought fire suppression expenditures to the forefront of budgetary and policy debate in the United States. Inasmuch as large fires are responsible for the bulk of fire suppression expenditures, understanding fire characteristics that influence expenditures is important for both strategic fire planning and onsite fire management decisions. These characteristics then can be used to produce estimates of suppression expenditures for large wildland fires for use in wildland fire decision support or after-fire reviews. The primary objective of this research was to develop regression models that could be used to estimate expenditures on large wildland fires based on area burned, variables representing the fire environment, values at risk, resource availability, detection time, and National Forest System region. Variables having the largest influence on cost included fire intensity level, area burned, and total housing value within 20 mi of ignition. These equations were then used to predict suppression expenditures on a set of fiscal year 2005 Forest Service fires for the purpose of detecting "extreme" cost fires—those fires falling more than 1 or 2 SDs above or below their expected value.

Keywords: Regression analysis, cost, fire characteristics

The severity of recent fire seasons in the United States has highlighted the extreme expenditures associated with wildland fire suppression. In fiscal years (FY) 2000, 2002, 2003, and 2006, fire suppression expenditures by the USDA Forest Service alone totaled about $1 billion annually. For the 10 years prior to 2000, fire suppression expenditures averaged around $350 million annually (in constant 2004 dollars). Along with the goal of diminishing the risk and consequences of severe wildland fires, the extreme expense of fighting these fires has become a driving force behind agency policy for some time. The desire to contain fire suppression expenditures motivates fuel treatments, affects suppression strategies and tactics, and helps define the relationship between the Forest Service and oversight agencies such as the Office of Management and Budget.

Large fires are responsible for the bulk of fire suppression expenditures (USDA Forest Service, USDA, and NASF 2003); therefore, understanding the characteristics of large fires is important for both strategic fire planning and onsite fire management decisions. Then, the characteristics can be used to predict suppression expenditures for individual, large fires. Currently, estimates of fire suppression expenditures for planning or decisionmaking are based on historical per acre expenditures or by selecting the firefighting resources to be used and arriving at an aggregate cost for these resources. Both have problems. Per acre expenditure estimates often are based on a small number of fires, in which their characteristics might vary dramatically from the fire in question. Aggregating the cost of selected fire suppression resources does not take into account the large overhead costs often associated with these larger fires. Developing regression models that take into account a variety of factors affecting suppression expenditures may be one way to improve these estimates (MacGregor and Haynes 2004).

Some research into developing statistical models to either predict fire expenditures or investigate causal factors of expenditures has been conducted. Donovan et al. (2004) used regression analysis to identify variables affecting suppression expenditures for 58 fires that occurred in Oregon and Washington in 2002. The only significant variables were fire size and terrain with measures of housing density, a focus of the study, not showing up as a significant predictor of costs. Steele and Stier (1998) developed a series of regression equations to estimate suppression costs for Wisconsin wildfires managed by the State Department of Natural Resources. Significant variables included final fire size and burning index. Earlier studies such as the one performed by Gonzalez-Caban (1984) attempted to estimate suppression expenditures based on the number and type of the different resources used on the fire, and it found considerable variation among fires and regions of the country.

In these analyses, it is important to differentiate between expenditures and economic costs. The actual cost of the fire has many components that are not accounted for by the suppression expenditures on the fire such as property-related losses, burned area emergency rehabilitation expenditures, long-term rehabilitation projects, water quality mitigation, business losses, and loss of recreation values. In our study, we made no attempt to account for all the costs associated with wildfires. When we use the word "cost" in this article, unless otherwise stated, we are talking about the expenditures to suppress the fire.

Using data on 1,550 fires reported by the Forest Service from FYs 1995–2004, we developed equations to predict fire suppression expenditures on a given wildfire based on fire characteristics that we hypothesized would affect expenditures and that were readily available or could be calculated with given information. Such equations could be used in prefire planning and real-time decision support

Received May 12, 2006; accepted August 31, 2006

Krista M. Gebert, USDA Forest Service, Rocky Mountain Research Station, Missoula, MT 59807, can be reached at kgebert@fs.fed.us. David E. Calkin, USDA Forest Service, Rocky Mountain Research Station, Missoula, MT 59807, can be reached at decalkin@fs.fed.us. Jonathan Yoder, Washington State University, School of Economic Sciences, Pullman, WA 99164, can be reached at yoder@wsu.edu.

systems. They also could be helpful for postfire analysis. Actual expenditures on individual fires in any given year could be compared with their "predicted" expenditures, and those fires with actual expenditures above a certain range (outliers) could be further reviewed to see why their costs were so high relative to other fires with similar characteristics. The statistical model presented in this study is designed to balance statistical performance with ease of use for prediction and analysis of fires beyond the sample used to estimate the parameters of the model.

Methods

We collected expenditure and fire characteristic data for large fires reported in the Forest Service's fire occurrence database, the National Interagency Fire Management Integrated Database (NIFMID), that could be accurately cross-identified with the Forest Service accounting system. We then developed and tested a theoretical model with suppression cost per acre as a function of the fire environment, values at risk, detection time, and resource availability for individual fires using ordinary least squares regression. Below we discuss the data collection process, the model and variables used, and the analysis methods.

Data Collection

Data were collected on fires reported in the NIFMID for FYs 1995–2004 (FY 1995 was the earliest year for which financial information was still available). Our analysis was restricted to fires that exceeded the "escaped" fire limit, defined by the Forest Service as greater than 100 ac before FY 2003 and greater than 300 ac since FY 2003. This restriction was necessary because smaller fires generally are assigned to a generic P-code for a region or forest, making it impossible to relate actual expenditures to individual fires and their characteristics (P-codes are the accounting codes the Forest Service uses to track expenditures on wildfires). Additionally, we used only fires where the Forest Service was the recorded protection agency because of the difficulty of obtaining expenditures by all agencies involved in a wildfire. We hoped that by making this restriction the Forest Service would have incurred the bulk of the expenditures on these fires, and we would lessen potential underestimation due to not accounting for the expenditures of other agencies. An earlier analysis of 216 fires, where expenditures for all agencies were obtained and the Forest Service was identified as the lead protection agency, showed that the Forest Service expended, on average, more than 90% of the money on these fires (Rocky Mountain Research Station, unpublished report, 2002). The remaining 10% was split between the Department of the Interior and state/local agencies.

Estimated suppression costs are available for most of the fires reported in the NIFMID or from the ICS-209 (the ICS-209 Incident Status Summary is used for reporting information on "incidents of significance" [USDA Forest Service 2004b]). However, through extensive use and analysis of the data, we believe that the cost estimates found in these reports are largely inaccurate and should not be used for analysis. For instance, in FYs 2000 and 2002, when the Forest Service spent more than $1 billion on suppressing wildland fires, the estimated costs in the NIFMID only totaled $655 and $629 million, respectively. The only accurate data on suppression expenditures are the actual expenditures obtained from the Forest Service accounting system, but there is difficulty matching these expenditures with specific fires. Starting in FY 2005, the P-code will be a required field in the NIFMID, making subsequent analysis of large fire expenditures much easier.

Fire complexes also cause problems when analyzing expenditures on individual fires. A fire complex is a group of fires that are administratively treated as one fire. There is no set rule for tracking expenditures on complexes, but, usually, expenditures for all fires in the complex are assigned to a single P-code. Where possible, we apportioned actual expenditures to the fires in the complex based on the estimated costs shown in the NIFMID and used these fires in our analysis. This was possible for approximately 80% of the identified fire complexes. For 17 fire complexes (comprised of 61 individual fires) this was not possible because of missing information or because we were unsure if we had accounted for all the fires in the complex. The necessary removal of these fires from the analysis is unfortunate because fire complexes often are some of the most expensive fires.

Our data collection requirements had the following effect on the number of fires available for analysis: fires reported in the NIFMID, 100,643; fires greater than 100 ac (or 300 ac depending on the year), 3,061; fires where the Forest Service was the recorded protection agency, 2,518 fires; remaining fires with useable P-codes, 1,644; final fires used in analysis, 1,550 (because of missing values for some variables). Rather than use other statistical methods for addressing the 94 observations with missing values (such as using the sample mean), we chose to eliminate these observations from the analysis. A regression relationship is conditional (conditioned) on the explanatory variables; therefore, selection of a sample from a population based on one or more explanatory variables is not a problem unless there is reason to believe that the random regression disturbance is in some way correlated with missing data. Given our knowledge of the data collection process, we see no reason why this would be the case.

The Model

The goal of fire suppression is to reduce resource damage from a natural hazard, in highly variable environments, with considerable uncertainty associated with such things as fire behavior and weather. Some fires, regardless of the amount of suppression resources used, will resist control. Others are relatively easy to suppress. We hypothesize that suppression expenditures are a function of environmental factors during the fire, the values at risk surrounding the fire, the availability of suppression resources, the initial suppression strategy, and the amount of time between ignition and discovery (delay). Therefore, a general form for a regression model to estimate the impacts of these variables can be summarized as

$$\text{suppression expenditures/area burned} = fn\,(\text{area burned, environment, values at risk, resource availability, initial suppression strategy, and delay}).$$

We use area burned, rather than fire perimeter, because perimeter information was not available for the majority of fires used in our analysis. Also, in practice, fire managers are accustomed to thinking in terms of cost per acre; therefore, cost per acre was used as the response variable rather than total cost.

Given that our observations are at the level of an individual fire, there is a potential problem with including fire size as an independent variable to explain cost per area burned. Standard fire economic theory implies that as more suppression effort is directed at a fire, area burned goes down—more money expended reduces area burned. Consequently, in principle, there may be a two-way causality: cost per acre affects area burned and area burned affects fire

Table 1. Variables used in development of regression equations [dependent variable = ln(wildland fire suppression expenditures/acre)].

Fire characteristics	Variable definition	Source
Size		
ln(Total acres burned)	Natural log of total acres within the wildfire perimeter	NIFMID
Fire environment		
Aspect	Sine and cosine of aspect at point of origin in 45° increments	NIFMID
Slope	Slope percent at point of origin	NIFMID
Elevation	Elevation at point of origin	NIFMID
Fuel type	Dummy variables representing fuel type at point of origin. Grass = NFDRS fuel models A, L, S, C, T, and N; Brush = NFDRS fuel models F and Q; slash = NFDRS fuel models J, K, and I; timber = NFDRS fuel models H, R, E, P, U, and G; brush4 (reference category) = NFDRS fuel models B and O	NIFMID
FIL	Dummy variable for FIL 1–6 (FIL 1 = reference category)	NIFMID
ERC	ERC calculated from ignition point using nearest weather station information (cumulative frequency)	Calculated
Values at risk		
ln(Distance to nearest town)	Natural log of distance from ignition to nearest census designated place	Calculated
ln(Total housing value 5)	Natural log of total housing value in 5-mi radius from point of origin (census data)/100,000	Calculated
ln(Total housing value 20)	Natural log of total housing value in 20-mi radius from point of origin (census data)/100,000	Calculated
Reserved areas	Dummy variables indicating whether fire was in a wilderness area, inventoried roadless area, or other special designated area (reference category = not in reserved area)	Calculated
ln(Distance to reserved area boundary)	If in a reserved area, natural log of distance to area boundary	Calculated
Detection time		
ln(Detection delay)	Natural log of hours from ignition time to discovery time	Calculated
$(\ln[\text{Detection delay}])^2$	Square of ln of detection delay	Calculated
Suppression strategy		
Initial suppression strategy	Dummy variables representing initial suppression strategy (confine, contain, and control) − reference category = control	NIFMID
Resource availability		
ln(Average deviation)	Natural log of the difference between the number of fires burning in the region during the period of the specified fire compared with the average in that region during the same time of year	Calculated
Region	Dummy variables for National Forest System region (reference category for western model = region 1 and for eastern model = region 9)	NIFMID

costs. If this two-way causality exists and is not accounted for in estimation, area burned is said to be *endogenous*, and the parameter estimates of the model are likely to be biased. However, large fires by their definition resist control. These events are very heterogeneous and, therefore, area burned may be more a function of fire complexity or potential than suppression effort, thus reducing the causal relationship between area burned and cost per acre. We pursue the standard approach, which is to test for endogeneity of area burned, and if it is found to be endogenous, then the use of an instrumental variables estimation method is warranted (Cameron and Trivedi 2005).

Explanatory Variables

Fire Environment

The environment in which a fire occurs can affect the difficulty and, therefore, the costs of controlling a wildfire. Characteristics such as rough or steep terrain, heavy fuel loads, and dry fuel conditions may increase unit suppression costs. A variety of fire characteristics that may affect suppression expenditures are available in the NIFMID or can be calculated using the information available there, including slope, aspect, elevation, fire intensity level (FIL), fuel type, and energy release component (ERC). Table 1 shows the fire characteristic information we extracted from the NIFMID for the fires in our database and the fire characteristics that were collected or calculated separately.

Topographic variables (slope, elevation, and aspect) are included because of the influence they have on fire behavior (all three are generally included in models of fire behavior such as FARSITE [Finney 2004]). Steeper slopes may cause fires to spread more rapidly, elevation can affect the amount of wind and moisture in an area, and south- and west-facing aspects often have lower humidity and/or higher temperatures. We hypothesize that the sign on elevation and slope will be positive, given no collinearity issues. Aspect, which is recorded in the NIFMID according to azimuth, was transformed to two variables—the sine and cosine of the azimuth (in radians; Mardia and Jupp [2000]) as opposed to using dummy variables for each aspect class, which would use up many more degrees of freedom. We hypothesize that the sign on the cosine and sine of aspect will be negative. A negative sign on these coefficients would increase costs for southern and western aspects where fuels are dryer and decrease it on eastern and northern aspects.

Fuel type also influences fire behavior and firefighting difficulty. We used five dummy variables to account for fuel type at the ignition point of the fire: grass, shrub, two brush variables, timber, and slash. The two brush models were brush and brush4, where brush reflected the National Fire Danger Rating System (NFDRS) fuel models F and Q (brush and dormant brush), and brush4 reflected NFDRS fuel models B and O (chaparral or heavy brush). Conversations with fire personnel identified these classifications as the most useful in determining required suppression effort (Merrill Saleen, National Interagency Fire Center, personal communication, Feb. 2, 2005). The reference category for fuels was brush4. We hypothesized that grass and brush would be less expensive than brush4 and timber and slash would be more expensive.

The other fire environment variable that came directly from the NIFMID, FIL, is an estimate of the fire behavior at the fire head during the first burning period and is based on the calculated flame length, where FIL 1 is 0–2 ft, FIL 2 is 2–4 ft, FIL 3 is 4–6 ft, FIL 4 is 6–8 ft, FIL 5 is 8–12 ft, and FIL 6 is greater than 12 ft. Because this is a categorical variable, it was transformed to five dummy variables, with FIL 1 being the reference category. We hypothesized that higher FILs would be associated with increased suppression costs because of the difficulties of fighting fire when extreme fire behavior is present.

To assess the effect of fire potential or fire danger on expenditures, in addition to FIL, we calculated an ERC index, which is a number related to the available energy (BTU) per unit area (square foot) within the flaming front at the head of a fire. It takes into account fuel moisture in both live and dead fuels and is a good reflection of drought conditions (National Wildfire Coordinating group 2002, California Board of Forestry 2004). ERC was calculated using Fire Family Plus (USDA Forest Service 2004a) with information from the weather station closest to the fire ignition point and based on Fuel Model G (Patricia Andrews, Rocky Mountain Research Station, personal communication, Aug. 20, 2003). Fuel model G was used because it has been found to be correlated with fire behavior in many areas of the country (Hall et al. 2005). The raw ERC value was converted to a cumulative frequency (the percentage of observations, based on local weather station information, that fall at or below the calculated ERC value) to better reflect fire conditions. We hypothesized that the sign on the coefficient for ERC would be positive: as fuel becomes drier, suppression becomes more difficult and costs increase.

Values at Risk

Areas with high values at risk such as private structures, public infrastructure, and high value timberlands are likely to command more suppression resources (USDA Forest Service 1995a, 1995b, National Academy of Public Administration 2002) and may, therefore, have higher costs than areas where fire is unlikely to cause significant resource losses. In fact, population encroachment into forested areas often is one of the factors used to explain the high costs of suppressing wildfires (Snyder 1999). Data on how much is spent to protect people and property are not readily available, so we assessed these effects indirectly using two different approaches: (1) calculating demographic characteristics within certain radii of fire ignition and (2) computing the distance to the nearest town. Using 2000 census data we calculated measures reflecting income (e.g., medium family income and per capita income), property values at risk (e.g., median housing value and total housing value), and total population for various radii around the fire ignition points: 5, 10, and 20 mi. All these variables were highly correlated with one another, and simple correlations showed total property values at different distances from the fire were most significantly correlated with suppression costs. Therefore, other demographic variables were omitted from the final model. We hypothesized that the total housing value variables would increase suppression costs and that distance from the nearest town would decrease costs.

Values at risk and the role of fire in land management may be substantially different between unreserved Forest Service lands and designated wilderness and roadless areas, resulting in fundamentally different suppression strategies. It is important to note, however, that wildland fire-use fires (naturally ignited fires that are managed to achieve resource benefits) were not contained in the dataset used for this analysis. Although 570 of the fires in our dataset began on reserved lands, these are fires in which active suppression took place. When this analysis was done, only 29% of Forest Service wilderness areas had approved fire management plans that allowed for the option of wildland fire use somewhere within their boundaries (Carol Miller, Aldo Leopold Wilderness Research Institute, personal communication, Jan. 20, 2004). Using the latitude and longitude of the fire ignition point, we calculated whether the fire started in one of these reserved areas and if it did, the distance to that area's boundary. These calculations were done for three categories of reserved lands: (1) wilderness areas, (2) inventoried roadless areas, and (3) other special designated areas such as wilderness study areas or national recreation areas. We also calculated the distance from the fire ignition to the nearest boundary of that particular area; e.g., for a fire starting in a wilderness area, the distance to the wilderness area boundary was calculated. Our hypothesis was that fires in reserved areas would be fought less aggressively and thus have reduced unit suppression costs (the sign on the dummy variables would be negative). We also hypothesized that fires further within the reserved area boundary would cost less than those closer to the boundary; fires closer to the boundary would be fought more aggressively because of increased risk of the fire traveling out of the reserved area.

Resources Available

The effect of resource availability on suppression costs is theoretically unclear. In one respect, having additional resources available may allow more rapid and efficient line construction and, therefore, reduce unit costs. However, it may be that the availability of resources may encourage excessive resource use due to a management incentive system that encourages risk-averse behavior and thus increases unit costs (Donovan and Brown 2005). Conversely, a lack of resources may dictate a revised and less-aggressive suppression strategy in some areas of the fire zone, resulting in a larger fire area, thus lowering unit costs.

We collected or calculated two variables to account for availability of resources. The first was the national preparedness level on the date of the fire ignition (National Interagency Fire Center 2004), but this variable was omitted from the final model because it was not statistically significant in preliminary regressions. The second variable, average deviation, estimates how many other fires were burning in the region at the same time as the fire in question, compared with the average number of fires that usually burn at that time of year. Our hypothesis was that if more fires were occurring than average for that time of year, firefighting resources might have been limited.

Following an analysis done by Lankoande (2005), we included delay, or response time, in the model. Delay was measured as the time from fire ignition to discovery, and it is expected (as Lankoande found) to be positive. We also included the square of delay because a scatterplot of delay and cost per acre indicated a possible quadratic relationship.

The final variable included in the model was initial suppression strategy (confine, contain, or control). According to the *FIRESTAT User's Guide* (USDA Forest Service 2003), these terms are defined as follows: (1) confine means to limit fire spread within a predetermined area principally by use of natural or preconstructed barriers or environmental conditions, (2) contain is the completion of a control line around a fire and any associated spot fires that can reasonably be expected to check the fire's spread, and (3) control is the completion of a control line around a fire and any associated spot fires that can reasonably be expected to hold under foreseeable conditions. We hypothesized that a more aggressive initial strategy (control) would

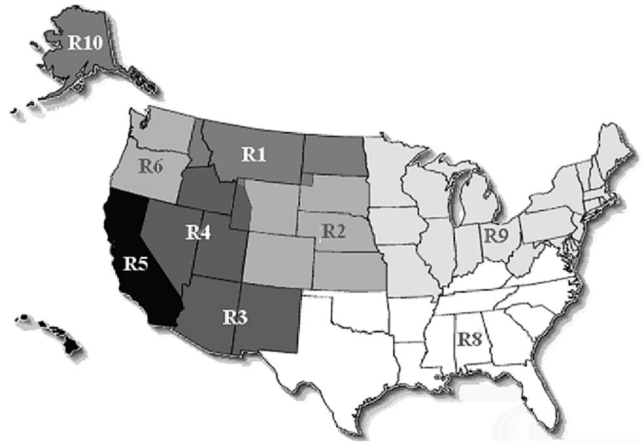

Figure 1. Map of USDA National Forest System regions.

increase cost per acre. It is important to note, however, that this is the strategy at the time the fire began. As the fire progressed, the suppression strategy may have changed.

Analysis

The results of our final analysis were two regional fixed effects models, one for the western United States (National Forest System Regions 1–6) and one for the eastern United States (National Forest System Regions 8 and 9; Figure 1). Statistical tests indicated that, at least for our dataset, it was not necessary to treat costs and acres as being simultaneously determined. A Wu-Hausman test failed to reject exogeneity of acreage for predicting cost per acre ($P > 0.23$).

All candidate independent variables were entered into the model to test significance. To develop a more parsimonious model, variables with a P value greater than 0.15 were removed one at a time, with the exception of categorical variables (such as fuel type) or other variables we felt should be treated as a group (such as housing values) with the model being reevaluated at each step. These groups of variables were handled differently. If F tests for joint significance showed that a group of related variables contributed to the model as a whole, then all variables within the group (except the reference variable in the case of categorical groups) were kept in the model regardless of their individual significance level.

Final model specification used a natural log transformation for the dependent variable (Forest Service expenditures per acre) as well as for most of the independent variables, with the exception of categorical variables. This model provided the best fit of the data and mitigated problems with heteroskedaticity among residuals. The general linearized model was

$$\ln(\$/\text{ac}) = B_0 + B_i^* \ln(X) + B_j^* Z,$$

where X are the fire characteristics to which we applied the natural log transformation (e.g., acres and distances), and Z were the variables that were not transformed, either because they were dummy or categorical variables or transformation did not appear to be indicated (such as slope and elevation). The percent impact of dummy variables is calculated following Kennedy (1981).

One final caveat about the estimated parameters follows from the fact that the sample is limited only to large fires. The consequence of this sample truncation is that the parameter estimates are not applicable to fires smaller than the lower limit of 100 ac. In addition, the parameter estimates for each variable given truncation are comprised of two parts: one represents the effect of a variable on the probability of being in the sample, and one represents the effect of the variable on the costs given that the fire size is big enough to be in the sample. Given that the primary purpose of this model is predictive, disentangling these effects on specific parameter estimates is of little importance, and we settled for the simpler linear specification rather than a truncated regression specification for the sake of pragmatic out-of-sample application of the model. Furthermore, exploratory regressions accounting for this truncation indicated that the estimated effects on the individual parameter estimates of this truncation are relatively small.

We do not feel that the differences in the lower bounds on acreage depending on year (100 ac versus 300 ac) should cause problems with the estimation process. There is no econometric/statistical problem, in principle, for having the sample based on the two different lower bounds as long as the same regression relationship holds for each subsample, which we found to be true in our preliminary investigations.

Table 2. Wildland fire suppression expenditures per fire and expenditures per acre for 1,550 large wildland fires, FY 1995–2004.

National Forest System region	Average cost per fire	Average cost per acre
	.... 2004 dollars	....
1	1,554,254	1,088
2	1,028,415	808
3	983,434	695
4	1,012,436	897
5	2,772,378	2,114
6	3,502,779	1,988
8	157,808	307
9	43,223	106

Results

The 1,550 fires analyzed in this study accounted for $2.07 billion of Forest Service suppression expenditures (in constant 2004 dollars) over the 7 years included in the sample. The average per fire cost was $1.3 million and the average cost per acre was $979 (both in constant 2004 dollars). Fires were distributed regionally as follows: Region 1, 217 fires; Region 2, 93 fires; Region 3, 222 fires; Region 4, 250 fires; Region 5, 199 fires; Region 6, 160 fires; Region 8, 309 fires; and Region 9, 100 fires. Table 2 shows average fire cost and cost per acre for each of the regions. One-factor analysis of variance indicated significant differences in both cost per acre and cost per fire among regions, with Regions 5 and 6 having significantly higher costs than Regions 1, 2, 3, and 4 and Regions 8 and 9 having significantly lower costs ($P < 0.001$ using Tukey's multiple comparison test).

Significant Variables and Their Affect on Cost

The final regression models for the West and the East are shown in Table 3, which lists the variables included, the estimated coefficients, and the P values. With the exception of elevation, all other variables (or groups of variables) were significant in at least one of the regression equations.

The size of the fire, in terms of area burned, has a negative effect on cost per acre, all else held constant. The interpretation for the coefficient on log transformed variables is that a 1% increase in the magnitude of the variable results in a B (the estimated coefficient)

Table 3. OLS regression models, western and eastern United States.

Variable	National Forest System Regions 1–6		National Forest System Regions 8–9	
	Coefficient	P value	Coefficient	P value
ln(Total acres burned)	−0.3238	0.000	−0.1941	0.006
Fire enviroment				
Aspect (cosine)	−0.1675	0.005	0.1009	0.263
Aspect (sine)	−0.1066	0.149	−0.4388	0.000
Slope	0.0057	0.003	0.0065	0.059
Elevation	Not in model		Not in model	
Grass	−0.5703	0.000	−0.5339	0.015
Brush	−0.3613	0.075	2.0391	0.026
Slash	0.2817	0.175	0.3503	0.261
Timber	0.5032	0.001	0.4981	0.038
FIL 2	0.8442	0.000	0.2206	0.265
FIL 3	1.3224	0.000	0.8458	0.000
FIL 4	1.6930	0.000	1.0424	0.000
FIL 5	1.8715	0.000	0.8160	0.010
FIL 6	1.7865	0.000	1.6956	0.000
ERC	0.0113	0.000	0.0047	0.112
Values at risk				
ln(Distance to nearest town)	Not in model		0.3029	0.014
ln(Total housing value 5)	0.0059	0.686	0.0329	0.188
ln(Total housing value 20)	0.1131	0.000	0.1703	0.098
Wilderness area	−0.2123	0.151	0.6703	0.017
IRA	0.1453	0.311	0.5806	0.213
Other SDA	0.1788	0.363	−0.6272	0.208
Wild × ln(distance to boundary)	−0.4309	0.000	0.7580	0.002
IRA × ln(distance to boundary)	0.0861	0.272	−0.1413	0.622
SDA × ln(distance to boundary)	−0.0905	0.313	−0.2781	0.187
Detection time				
Ln(Detection delay)	0.0353	0.171	−0.1859	0.000
Square of ln(detection delay)	−0.0184	0.037	0.0581	0.001
Suppression strategy				
Initial suppression strategy: confine	Not in model		0.6958	0.000
Initial suppression strategy: contain	Not in model		1.0056	0.002
Resource availability				
ln(Average deviation)	−0.0970	0.093	Not in model	
Region				
Region 2	−0.5398	0.016		
Region 3	−0.0792	0.643		
Region 4	0.1283	0.446		
Region 5	0.9631	0.000		
Region 6	0.9697	0.000		
Region 8			0.8122	0.000
Constant	4.587	0.000	0.3919	0.699

(Dependent variable = ln(wildland fire suppression expenditures/acre), R^2 (West) = 0.44, R^2 (east) = 0.49, n (West) = 1141, n (East) = 409), RMSE (West) = 1.5086 RMSE (East) = 1.1308. IRA, inventoried roadless areas; OLS, ordinary least squares; SDA, special designated areas.

percent change in the dependent variable (Gujarati 1988). Therefore, in the western model, a 1% increase in acres burned decreases cost per acre 0.32%. In the eastern model, the effect of acres is less pronounced, with a 1% increase in acres resulting in a 0.18% decrease in costs. However, it is important to remember that fire size in the East tends to be smaller and less variable than in the West. For the fires in our analysis, the average fire size in the East was 605 ac, compared with 4,700 ac in the West. There are several reasons given in the literature for the drop in cost per acre as fire size increases. Smith and Gonzalez-Caban (1987) state that most fire suppression activities are adjacent to the fire perimeter and because the ratio of the perimeter to area decreases as area increases, cost per acre should decline. Schuster et al. (1997) attribute this decline to economies of scale and more unburned areas within the perimeter of larger fires.

Looking next at those variables representing the fire environment, all except elevation were included in the final model. All other variables (or groups of variables) were statistically significant and for the most part had the expected signs. For aspect, because we used the sine and cosine of the azimuth (converted to radians) as the independent variable, the results are somewhat difficult to interpret: one must take the sine and cosine of the aspect (in radians), multiply the results by the respective coefficients, and add together. However, negative signs on both coefficients would support our hypothesis, with southern and western aspects having higher costs. For the western model, the coefficient on the cosine of aspect was indeed negative and statistically significant ($P = 0.005$). The coefficient of the sine of aspect also was negative, although not statistically significant ($P = 0.149$). However, for the eastern model, the coefficient on the cosine of aspect was positive but statistically insignificant ($P = 0.263$) and much smaller in magnitude than the coefficient on the sine of aspect. Because of this, by the time the two parts were added together, the effects in the East were, for the most part, consistent with those in the West, with fires with a southeastern, southern, southwestern, and western aspect having higher costs and fires with an eastern, northeastern, northwestern, or northern aspect having lower cost per acre.

Slope has a positive effect (as expected) on cost per acre in the West with a 1-unit change in the slope percent increasing costs by 0.57% in the West. For instance, a fire with a slope of 35% compared with one with a slope of 10% would cost approximately 15%

more, all else held constant. Slope was not statistically significant in the eastern model.

Fuel type had a very similar effect on cost for the West and the East. In the West, fires starting in timber cost 61% more than the reference category (brush4, heavy brush). In the East, the results were very similar, with timber fires being 62% more expensive than the reference category. Grass fires were the least expensive in both models, being 45% less expensive than the reference category in the West and 44% less expensive in the East. In both models, the coefficients on slash were statistically insignificant but comparable in magnitude. However, for the brush fuel model, the results were very different. This is because in the East, there was only one fire that started in brush (low or moderate brush), and it was a very expensive fire. Therefore, the coefficient on brush for the East showed that this fire was 465% more expensive than the reference category (heavy brush or chaparral). In the West, brush fires were 33% less expensive than the reference category.

FIL was a highly significant variable in both the western and the eastern models. All FILs were significantly more expensive than the reference category, FIL 1. As the FIL categories increase, cost per acre tends to increase. For the western model, the increase in cost per acre ranged from 127% for FIL 2 (compared with FIL 1) to a 539% increase in cost per acre for FIL 5 (FIL 6 was slightly lower at 486%). In the East, the magnitudes for FILs 2–4 were much smaller, ranging from a 33% increase in cost per acre for fires with FIL 2 (compared with FIL 1) up to a 204% increase for FIL 4. For FIL 6 the effect was similar to the West, increasing costs by 467% compared with the base case. However, in the East, fires with FIL 5 were less expensive than either FIL 4 or FIL 6 fires, increasing cost per acre 123% compared with the base case.

The last fire environment variable that was included in the model was ERC. Holding all else constant, an increase in the ERC increases costs 1.13% for every 1-unit increase in ERC (calculated as a cumulative frequency) in the West and 0.41% in the East. So, e.g., a western fire with an ERC in the 95th percentile, compared with the 80th, would have a cost per acre that was approximately 17% higher.

The next set of variables dealt with values at risk. The only surprising finding was that in the eastern model, as the distance to the nearest town increases, so do costs, with a 1% increase in the distance increasing costs by 0.31%. We expected this sign to be negative, indicative of fewer values at risk the farther you are from a populated place. Collinearity diagnostics did not indicate any problems with collinearity in the model. Therefore, it may be that in the East, with its more dense population, the farther from a town that the fire starts, the farther from firefighting resources and the more expensive the fire.

The total housing values within 5 and 20 mi of fire ignition were included in the models as a set, because statistical tests indicated that their predictive power was higher than if only one was used. Both variables suggest that as housing values increase, so do costs; however, only the housing value within 20 mi of fire ignition was statistically significant. Because of the magnitude of the numbers, we calculated total housing value in units of $100,000. In the West, for every 1% increase in total housing value (in units of $100,000) within 20 mi of fire ignition, cost per acre increases 0.11%. This seems like a small number, but given the magnitude of the housing values, it can add up quickly. The average total housing value within 20 mi of ignition for Regions 1–6 is over $3 billion. The maximum is $129 billion, and the minimum is around $450,000.

The variables representing whether or not the fire occurred in one of three reserved areas and the distance to the area boundary were all entered as a group and were retained, regardless of significance level. The only variables in the group that were statistically significant were whether or not the fire was in a wilderness area and the distance to the wilderness area boundary. In the western model, distance to the wilderness boundary had a statistically significant negative effect on cost. This conformed to our hypothesis that wilderness fires would be less expensive, especially the farther away the fire was from the wilderness boundary. In the eastern model, however, the opposite was true. If a fire started in a wilderness area, it was 86% more expensive than a fire not starting in the wilderness (all else constant) and the cost increased 0.72% for every percent increase in the distance to the wilderness boundary. This is comparable with the result for distance to the nearest town that we found in the eastern model, another indicator that in the more populated East, fires in more remote areas are more expensive to control.

The time between fire ignition and discovery time increased costs in the West and decreased costs in the East (although the coefficient for the western model was not statistically significant). The quadratic terms, however, were statistically significant in both models, although of different signs. The combined effect of the two terms showed that in the western model, costs increase as delay increases until delay is more than approximately 6.3 hours, and then cost per acre starts to decrease (average delay was 25.2 hours). In the eastern model, delay decreases cost per acre until the delay in hours is more than approximately 22.6 hours, at which time cost per acre starts to increase (average delay was 10.5 hours).

Initial suppression strategy (which is defined as confine, contain, or control) was not statistically significant in the western model. However, in the East, an initial strategy of confine increased costs 100%, relative to a strategy of control (the base case). A strategy of contain (as opposed to control) increased cost per acre by 173%. This is not the expected effect; control (the base case) is the most aggressive strategy, and we would expect it to cost more.

Resource availability, as measured by the variable average deviation, was not statistically significant in the eastern model, and in the western model, it was statistically significant only at the $P = 0.10$ level. The negative coefficient indicates that as the number of fires burning in the region increases by 1%, relative to the average for that time of year, cost per acre decreases by 0.097%. This would be consistent with a hypothesis that more fires mean fewer resources available to put on each fire (lower cost) and potentially a larger area burned, resulting in a lower cost per acre.

Estimating Suppression Expenditures

The main objective of this study was to produce regression equations that could be useful for predicting suppression expenditures on individual large fires. We developed a model using fire characteristics that were hypothesized to influence suppression expenditures such as fire behavior, difficulty of the firefighting environment, proximity to values at risk, and resource availability, while also controlling for size. The variables used, for the most part, conformed to our understanding of how they might affect expenditures, and we feel, therefore, that the relationships we found can be useful in explaining expenditures on large wildland fires.

We used these equations to make out-of-sample predictions for large FY 2005 fires. The R^2 between the observed and predicted values in sample (FY 1995–2004) was 0.45 for the western model and 0.46 for the eastern model. For the out-of-sample predictions, it

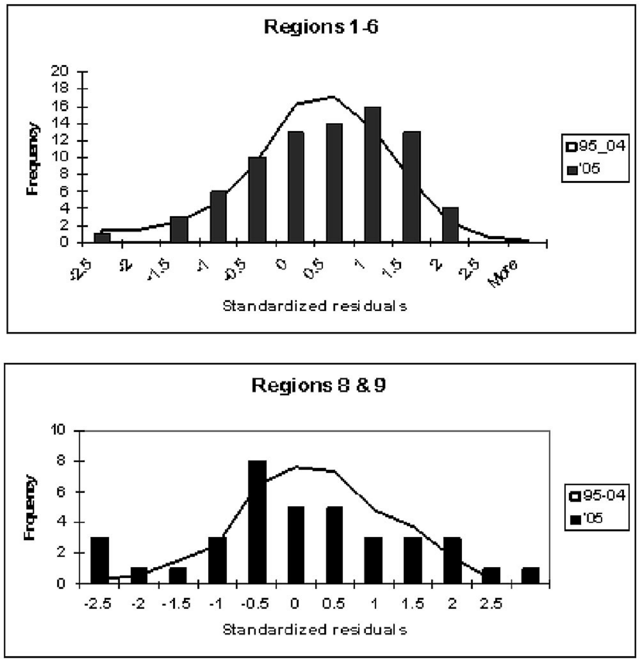

Figure 2. Standardized residuals from wildland fire suppression expenditure regressions, historical (1995–2004) versus FY 2005.

was 0.33 for the western model, but only 0.18 for the eastern model. Why the substantially poorer performance of the eastern model for FY 2005? Figure 2 shows the standardized residuals from both the in-sample and out-of-sample predictions. For the western model, the two distributions are very similar and chi-square tests showed no statistical difference between the two distributions ($P = 0.51$). For the West, the relationships between fire characteristics and costs found in the historical data seemed to follow through into FY 2005. However, for the East, we do see a noticeable difference in the distributions for FY 2005 compared with the historical data. There are more fires at each end of the distribution in FY 2005 compared with the historical distribution and a lot fewer fires in the middle section of the distribution, especially on the right side. The chi-square tests confirmed that the two distributions are significantly different ($P = 0.001$), with the biggest difference occurring in the very low cost fires. This may represent a change in how fires are being fought in the East or perhaps just a fire season that was very dissimilar to those occurring from FYs 1995–2004.

The estimated equations can be useful for identifying fires within or outside the original model estimation sample in which their costs fall outside a "normal range," given a specific set of fire characteristics. To do so, we identified FY 2005 fires where the actual cost per acre fell 1 or 2 SDs above or below the predicted cost (both in terms of the natural log of cost per acre), given the fires explanatory characteristics. For FY 2005, we identified 12 fires that fell outside the 2 SD range; six with higher than expected expenditures and six with lower than expected expenditures (out of 117 total fires).

These fires can then be reviewed further to see why they cost so much more (or less) than other fires with similar characteristics. For some of these "outlier" fires, the extreme difference between expected and actual costs may be due to the fact that the equations are built using information available at the start of the fire—nonspatial information based on characteristics at the ignition point of the fire. For instance, a fire may have started out in grass but burned predominantly in timber. The model would, therefore, underpredict the cost of this fire. However, on review of the fire, the cause of the extreme cost would be easily discernible. This was the case for a particular fire that we looked at in more detail because of a fire review that was being done. The predicted cost per acre was based on the fuel type at the ignition point, which was grass. However, if the fuel type was changed to timber (which we found out was the predominant fuel type), the predicted value would have increased by nearly 200% and the predicted cost would have been almost identical to the fire's actual cost. Therefore, this fire was designated as an outlier simply because of the nature of the fire occurrence data. However, for other fires the cause may not be related to the nonspatial nature of the data, but rather to policy issues that are not readily captured by the variables available for this study. The decision to fight fires aggressively because of political or jurisdictional issues is not captured in any of the fire databases. However, by further reviewing "outlier" fires, such expenditure patterns may become apparent. Additionally, analysis of the "low cost" fires could lead to the discovery of firefighting strategies or cost-saving techniques that could be applied to other fires.

For the process of identifying outliers as discussed previously in this article, we used the results from the original log-linear model, which provides linear predictions of the *natural log* of cost per acre, *not* cost per acre itself. To get predictions for cost per acre in dollar values, it is tempting to simply exponentiate the predicted values from the log-linear regression. However, this provides a biased and inconsistent estimate of cost per acre. There are a number of methods to adjust for this bias. The smearing estimator (Duan 1983) is derived by multiplying the retransformed predicted values, $\exp(\hat{y})$, by a *smearing correction factor*, which is the average of the retransformed residuals, $\exp(\hat{e})$. Another estimator (often called the "naive" estimator) assumes normally distributed errors and is calculated as $\exp(\hat{y} + \hat{\sigma}/2)$, where $\hat{\sigma}$ is the estimated standard error of the regression residuals. The calculated smearing correction factors for the western and eastern models were 2.476 and 1.83, respectively. The naive correction factor (the estimated error variance divided by two) was 1.137 for the western model and 0.639 for the eastern model.

Predicted costs using the two correction methods and with no bias correction were generated and compared using the (out-of-sample) 2005 data. For both models, summary measures such as root mean square error (RMSE) indicated that the results with no bias correction produced better estimates, with the smearing estimator coming in second, and the naive correction coming in third. The RMSE for the uncorrected predictions was \$54, for the smearing estimator it was \$69, and for the naive estimator it was \$86. For the eastern model, the RMSE for the uncorrected predictions was \$35, for the smearing estimator it was \$59, and for the naive estimator it was \$61. These results indicate that, in practice, for the models developed in this study, the uncorrected predictions produce better predictions for the 2005 data. However, this result will not necessarily be true for other samples, and the theoretical bias and inconsistency of the uncorrected predictions still holds.

Another issue to recognize when using these models for predicting suppression expenditures is the large confidence intervals for the predictions that follow primarily from the large residual variation in costs. For instance, for the FY 2005 fires, the mean predicted value was \$317/ac with a ± 1 SD (68%) range of \$88–1,132. This large range in predicted costs must be recognized when using these models for wildland fire decision support.

Discussion

In this study we found statistical evidence that factors often used to explain high and rising costs of fire suppression do indeed seem to be an important determinant of fire expenditures. Variables related to fire risk or potential such as FIL and ERC were positively related to fire expenditures, and in the case of FIL, had a large effect on cost per acre. Wildland-urban interface issues also were found significantly related to fire expenditures in the West. As the total housing value within 20 mi of the fire ignition point increases, cost per acre increases. Characteristics such as housing value, however, are not really under the control of land managers. It would be useful to start collecting data on other factors that may be alterable to see their effect on suppression expenditures. Examples might include condition class: primary objectives of fire suppression (why is the fire being suppressed) that could include categories such as protecting lives, protecting property, preventing spread onto another agencies land, protecting threatened and endangered species habitat, and so on, ranked by importance; location of past fuel treatments; amount of effort expended on structure protection; road access; resources used—not just type and number, but hours; and information on the incident management team type assigned to the fire.

Additionally, improvements in the data would likely improve the estimates and add to our understanding of the factors influencing suppression expenditures. Such improvements might include developing a truly interagency fire occurrence data system with links to the financial system and more spatially explicit data that includes fire perimeter information and fire characteristics over a broader landscape than just at the fire ignition point.

Equations such as those developed in this study could be used to flag outliers or fires with extremely high or low costs compared with what would be expected, as we did for the FY 2005 fires. By further reviewing these fires, more information may be obtained on the issues associated with suppression expenditures on large wildland fires. This could lead to the identification of other data that could be easily collected on wildfires and lead to improvements in estimates of wildland fire expenditures. However, it also is possible that the review of such fires could lead to the identification of policy or political issues that need to be dealt with before large gains in containing suppression expenditures can be realized.

Literature Cited

California Board of Forestry. 2004. *California fire plan.* Available online at www.fire.ca.gov/FireEmergencyResponse/FirePlan/appendixb.html; last accessed Oct. 26, 2004.

Cameron, C., and P. Trivedi. 2005. *Microeconometrics: Methods and applications.* Cambridge University Press, Cambridge, United Kingdom. 1034 p.

Donovan, G.H., P. Noordijk, and V. Radeloff. 2004. Estimating the impact of proximity of houses on wildfire suppression costs in Oregon and Washington. In *Proc. of 2nd Symp. on Fire economics, planning and policy: A global view, Cordoba, Spain, Apr. 19–22, 2004.* [CD Rom, USDA Pacific Southwest Res. Stn., Riverside, CA].

Donovan, G.H., and T.C. Brown. 2005. An alternative incentive structure for wildfire management on national forest land. *For. Sci.* 51(5):387–385.

Duan, N. 1983. Smearing estimate: A nonparametric retransformation method. *J. Am. Stat. Assn.* 78(383):605–610.

Finney, M.A. Revised 2004. *FARSITE: Fire Area Simulator—model development and evaluation.* USDA For. Serv. Res. Pap. RMRS-RP-4. 47 p.

Gonzalez-Caban, A. 1984. *Costs of firefighting mopup activities.* USDA For. Serv. Res. Note PSW-367. 5 p.

Gujarati, D.N. 1988. *Basic econometrics,* 2nd Ed. McGraw-Hill, New York. 145–148.

Hall, B.L., T.J. Brown, and L.S. Bradshaw. 2005. *Development of U.S. operational fire danger 15-day forecasts.* CEFA Rep. 05-02. Desert Research Institute, Program for Climate, Ecosystem, and Fire Applications. 19 p. Available online at www.cefa.dri.edu/Publications/ Task09_report.pdf; last accessed Apr. 2006.

Lankoande, M.D. 2005. *Three essays on wildfire economics and policy.* PhD dissertation, Washington State Univ., Pullman, WA. 68 p.

Kennedy, P. 1981. Estimation with correctly interpreted dummy variables in semilogarithmic equations. *Am. Econ. Rev.* 71(4):801.

MacGregor, D.G., and R.W. haynes. 2005. *Integrated research to improve fire management decisions.* USDA For. Ser. Gen Tech. Rep. PNW-GTR-630. 28 p.

Mardia, K.V., and P.E. Jupp. 2000. *Directional statistics.* John Wiley and Sons, Ltd., New York. 429 p.

National Academy of Public Administrators. 2002. *Wildfire suppression: Strategies for containing costs.* NAPA, Washington, DC. 180 p.

National Interagency Fire Center. 2004. What are preparedness levels? Available online at www.nifc.gov/fireinfo/pl_desc.html; last accessed Oct. 26, 2004.

National Wildfire Coordinating Group. 2002. *Gaining an understanding of the national fire danger rating system.* Available online at www.famweb.nwcg.gov/pocketcards/master_gaining.pdf; last accessed Apr. 2006. 82 p.

Schuster, E.G., D.A. Cleaves, and E.F. Bell. 1997. *Analysis of USDA Forest Service fire-related expenditures 1970–1995.* USDA For. Serv. Res. Pap. PSW-RP-230. 29 p.

Smith, E.L., and A. Gonzalez-Caban. 1987. *Estimating cost of large-fire suppression for three Forest Service regions.* USDA For. Serv. Res. Note PSW-391. 5 p.

Snyder, G.W. 1999. Strategic holistic integrated planning for the future: Fire protection in the urban/rural/wildland interface (URWIN). P. 159–170 in *Proc. of the Symp. on Fire economics planning, and policy: Bottom lines,* Gonzalez-Caban, A., and P.N. Omi (tech. coords.). Pacific Southwest Res. Stn., Albany, CA. USDA For. Serv. Gen. Tech. Rep. PSW-GTR-173.

Steele, T.W., and J.C. Stier. 1998. An economic evaluation of public and organized wildfire detection in Wisconsin. *Intern. J. Wildland Fire* 8(4):205–215.

USDA Forest Service. 1995a. *Fire suppression costs on large fires: A review of the 1994 season.* USDA For. Serv., Fire and Aviation Management, Washington, DC. 18 p. + appendix.

USDA Forest Service. 1995b. *Strategic assessment of fire management in the USDA Forest Service.* USDA For. Serv., Washington, DC. 30 p.

USDA Forest Service. 2003. *FIRESTAT user's guide: Version 5.4.* USDA For. Serv., Fire and Aviation Management, Washington DC. 145 p.

USDA Forest Service. 2004a. *Fire family plus, version 3.0.5.0.* USDA For. Serv. Rocky Mountain Res. Stn., Missoula, MT.

USDA Forest Service. 2004b. *209 Program user's guide.* Available online at www.fs.fed.us/fire/planning/nist/209_UserGuide.pdf; last accessed Apr. 2006. 126 p.

USDA Forest Service, USDA, and NASF. 2003. *Large fire cost reduction action plan.* Available online at www.fs.fed.us/fire/management/action_ plan/cost_ reduction.html; last accessed Apr. 2006.