Wildfire Suppression Cost Forecasts for the US Forest Service

Karen L. Abt, Jeffrey P. Prestemon, and Krista M. Gebert

ABSTRACT

The US Forest Service and other land-management agencies seek better tools for anticipating future expenditures for wildfire suppression. We developed regression models for forecasting US Forest Service suppression spending at 1-, 2-, and 3-year lead times. We compared these models to another readily available forecast model, the 10-year moving average model, and found that the regression models do a better job of forecasting the expenditures for all three time horizons. When evaluated against the historical data, our models were particularly better at forecasting the more recent years (2000–2007) than the less sophisticated models. The regression models also allowed us to generate, using simulation methods, forecast statistics such as the means, medians, and confidence intervals of costs. These additional statistics provide policymakers, wildfire managers, and planners more information than a single forecast value.

Keywords: expenditures, budget, wildland fire management

Uncertainty regarding future wildfire suppression expenditures presents an ongoing challenge to policymakers and agency administrators within the US Forest Service and other land-management agencies. As part of the federal budgetary process, the land-management agencies must provide estimates of the funding needed to suppress wildfires 3 years before the season begins. This requested amount is based, in part, on a 10-year moving average of historical suppression costs. For 8 of the last 10 years, however, the funds requested by the US Forest Service have fallen short of the amount needed for wildfire suppression. Part of the rise in suppression costs can be explained by increases in area burned, which are linked to climate shifts (e.g., Swetnam and Betancourt 1990), and drought patterns that favor greater wildfire activity (e.g., Westerling et al. 2003, Siebold and Veblen 2006).

Because federal agencies are not allowed to spend more money than they have been appropriated, shortfalls in suppression expenditures must be made up by transferring money from other US Forest Service programs or by requesting additional funds from Congress. Transfers from other US Forest Service programs, even if these funds are eventually restored by Congress, have been shown to interfere with overall agency operations (US General Accounting Office 2004). This makes the estimate of future suppression spending a critical part of both wildfire management and overall agency planning.

To monitor possible budget shortfalls, Gebert and Schuster (1999) developed within-season expenditure forecasts, which are now used by both the US Forest Service and the Department of Interior to monitor spending during the height of the fire season (June through September). In addition, Prestemon et al. (2008) developed forecasts for 1 year ahead using climate, drought, and trend variables to forecast suppression expenditures for the current fiscal year (FY). Abt et al. (2008) developed autoregressive time series regressions to forecast suppression costs 2 and 3 years in advance.

This article reports on improved 1-, 2- and 3-year-ahead regression model forecasts of US Forest Service wildfire suppression expenditures. We describe the improvements over models initially reported by Abt et al. 2008 and Prestemon et al. 2008 and describe their forecast accuracy. The regression models are also compared with the 10-year moving average forecast model. In an application of the latest model developments, we report forecasted expenditures for FY 2008, 2009, and 2010, and we compare the 2008 forecast with actual 2008 expenditures.

Developing Statistical Expenditure Forecast Models

There are many types of models that could be used to develop a statistical forecast of wildfire suppression expenditures, including those based on averages of historical

costs, pure autoregressive models of historical costs, and more complex regression models that may include historical costs but also external information. The first approach is the simplest, and one example is the 10-year moving average of the most recent observed costs. This model gives each year an equal weight when making forecasts and implicitly assumes that expected costs change slowly. In addition, relatively simple are autoregressive models, which are similar to moving average models except that they allow previous years' costs to have differing weights. These two approaches require no data other than the time series of costs and may have an added benefit of relative transparency, but they may ignore potentially useful external information. The more complex regression models take advantage of this additional external information.

For this analysis, the cost of fire suppression is defined as the group of expenditures that fall under the US Forest Service budget category of Wildland Fire Suppression. This includes money expended to suppress wildland fires, to monitor naturally occurring fires that are being allowed to burn for resource benefits, and emergency rehabilitation of burned areas. This definition does not include physical or economic damages to trees, forests, structures, or the impacts on the local economy from either the wildfire or suppression operations. In this article, we use the terms suppression cost and suppression expenditure interchangeably. Our expenditure data are from a database of US Forest Service fire management expenditures first developed by Schuster et al. (1997) and maintained by the Rocky Mountain Research Station. The data, which extend for 31 years (1977–2007), are annual by US Federal FY, which begins October 1 and ends September 30. For example, FY 2007 began Oct. 1, 2006 and ended Sept. 30, 2007.

Suppression expenditures are influenced by a number of factors. Anything that affects the number, size, and intensity of wildfires will affect the costs of suppression. Our regressions include ocean temperatures and ocean pressure indices that have been shown to influence fire in many parts of the United States. Sea surface temperatures and atmospheric pressure affect circulation patterns, including frontal systems and thunderstorms, thus affecting fire-related weather and hazardous forest fuels by altering lightning, precipitation, temperature, and wind. These include the El Niño-Southern Oscillation (Swetnam and Betancourt 1990, Barnett and Brenner 1992, McKenzie et al. 2004, Schoennagel et al. 2005, Kitzberger et al. 2007), the Pacific Decadal Oscillation (McKenzie et al. 2004, Schoennagel et al. 2005, Collins et al. 2006, Kitzberger et al. 2007), the Arctic Oscillation, the Southern Oscillation Index (Simard et al. 1985, Swetnam and Betancourt 1990, Brenner 1991), and the North Atlantic Oscillation (Collins et al. 2006, Kitzberger et al. 2007).

Although larger climatic patterns are represented by the ocean temperature and pressure measures, we also incorporate localized measures of drought to capture the local effects of changes in precipitation and temperature on fuel conditions. Drought indices have been shown to explain observed fire activity (Westerling 2003, Crimmins and Comrie 2004, Gedalof et al. 2005, Collins et al. 2006).

We also included a trend variable in each of the regressions to capture systematic changes in capital and labor prices and regional populations. Early tests of the energy price index did not show any correlation with suppression costs. The expenditures made in previous years were also included in the regressions to capture persistent spending patterns that may be related to management practices and cost structures. Insignificant variables (trend, drought, climate, and previous expenditures) were dropped from the forecasting models.

Estimating Statistical Expenditure Forecast Models

We developed three different multi-equation models, with the equations within each model corresponding to different US Forest Service administrative units that are believed to have different wildfire systems or expenditure patterns. The 1-year-ahead forecast model divided the United States into four geographic regions and a catchall category called Rest of the Forest Service, which encompassed suppression-related expenditures made by national offices and research stations. For the 1-year-ahead model, our tests found that combining the six western regions into a single equation (Western Aggregate, including the Pacific Southwest, Pacific Northwest, Intermountain, Northern, Rocky Mountain, and Southwest regions) improved the forecasts. In the models for 2 and 3 years ahead, each of the nine geographic regions (Alaska, Southern, Eastern, Rocky Mountain, Pacific Southwest, Pacific Northwest, Northern, Southwest, and Intermountain) and the Rest of the Forest Service are tracked by 10 separate equations.

The modeling process included several steps. First, each of the regional or regional-aggregate equations within a model was specified separately to identify the variables that do the best job of explaining costs. Second, the regional equations were estimated together to account for any correlations in costs beyond those explained by the variables included in each regional equation. Third, a predicted value was developed for every year (FY 1977–2007), including the forecast years (FY 2008–2010). Fourth, to make an agencywide forecast of suppression costs for future years, we forecasted costs for each region or regional aggregate and then added those costs together to arrive at a total predicted value for the year. Fifth, prediction errors for all the equations in each model were used to generate confidence intervals, as well as mean and median forecast values around the predicted values of the costs of future seasons. Each of these steps is further described in the following sections.

Step 1. All 25 equations were initially specified with the following variables: lagged suppression costs (one to seven years back), lagged monthly Palmer Drought Severity Index (the Palmer X series for the 1-year-ahead model and the Palmer H series for the 2- and 3-year-ahead models) (National Oceanic and Atmospheric Administration [NOAA] 2007a); lagged ocean temperatures and pressures indices (including the North Atlantic Oscillation [NOAA 2007b]), the Pacific Decadal Oscillation (Mantua and Hare 2007), Niño-3 sea surface temperature anomaly (NOAA 2007c), the Southern Oscillation Index (NOAA 2007d), and the Arctic Oscillation (NOAA 2007e); and a trend variable. Forecasts of the El Niño-Southern Oscillation (made as forecasts of the Niño-3 sea surface temperature anomaly) were only included in the 1-year-ahead model because forecasts are not available for more than 1 year ahead (Wang 2006, NOAA 2007f). Interactions between the climate measures are common, and further discussion of these interactions can be found in a study by Prestemon et al. (2008).

We were unable to correct anomalies in the suppression cost data that resulted from accounting adjustments. Thus, we included dummy variables, equal to one for the year and the region in question and zero other-

wise, to isolate the effect of these accounting anomalies.

Another adjustment we made was in recognition of work by Calkin et al. (2005) and Westerling et al. (2006), which identified a significant shift in wildfire activity in the western United States that occurred in the mid-1980s. We tested for a change between pre- and post-1986 and found significance in one of the 2-year-ahead models (California) and in four of the 3-year-ahead models (California, Eastern, Alaska, and Rest of the Forest Service), so an additional dummy variable measuring this shift was included in those regions' equations.

Step 2. In selecting a final set of variables to include in the forecast equations, variables different from zero at weaker than 20% significance were dropped from the initial full specification. Once the independent variables were determined for each regional equation in a model, the equations were estimated together (5 equations in the 1-year-ahead model, 10 equations in the 2-year-ahead model, and 10 equations in the 3-year-ahead model) as seemingly unrelated regressions. This estimation process accounts for correlations of random errors in costs across the equations of a model and thereby reduces parameter estimation uncertainties.

Step 3. Forecast values for each FY from 1977 to 2007 were produced by a jackknife procedure using the 1-, 2-, and 3-year-ahead forecast models. The jackknife procedure estimates parameters by leaving out 1 year, and then uses these parameter estimates to forecast the cost for the year that was left out. For example, to produce the jackknife forecast for the 1-year-ahead model for, say, FY 1999 for the Western Aggregate, we used data for all years except 1999 to estimate the parameters of the 1-year-ahead model. We then used these parameter estimates and the actual 1999 values of the independent variables to forecast the 1999 suppression cost. We repeated this process for all years from FY 1977 to 2007.

Step 4. The forecasts from each of the equations were added together to produce a single agencywide forecast of suppression costs for each year from FY 1977 to 2007. All forecasts and actual expenditures are reported in inflation-adjusted (2004) dollars (US Department of Commerce 2007).

Step 5. To quantify the uncertainty of the FY 2008, 2009, and 2010 suppression costs, we used the uncertainty contained in the equations of the individual regressions in
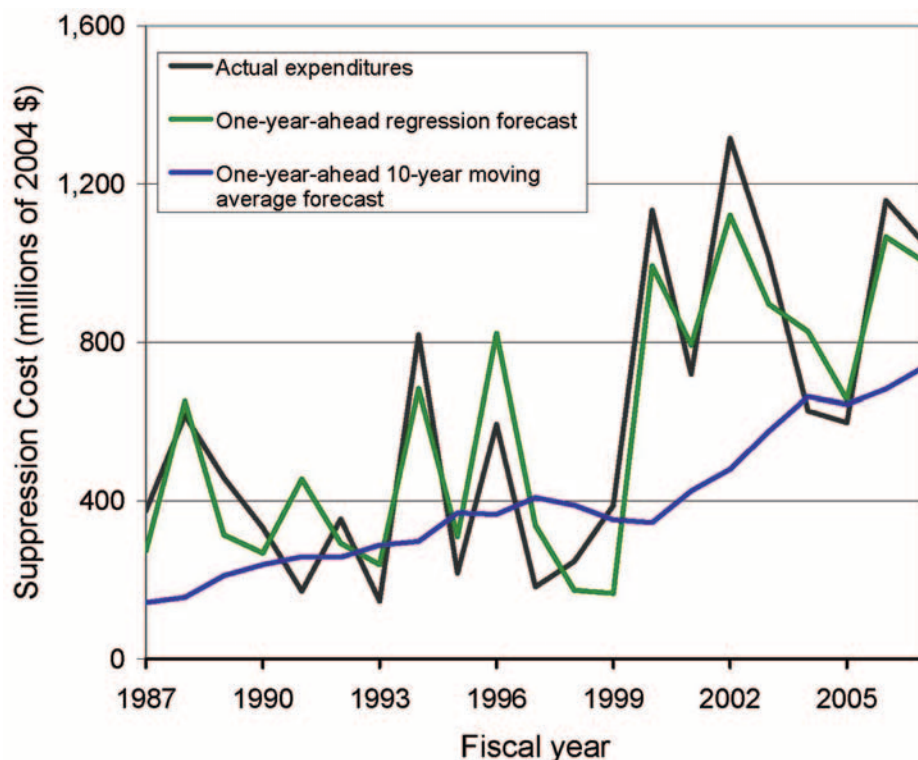

Figure 1. Comparison of actual expenditures to 1-year-ahead forecasts from the regression model and the 10-year moving average model for FY 1987–2007.

a simulation to generate a probability distribution of possible suppression costs. Prestemon et al. (2008) provide additional details on the generation of this distribution. The simulations produce estimates of the median and mean forecast values, as well as the 90 and 95% confidence intervals for the 1-, 2-, and 3-year-ahead forecasts.

Regression and Forecast Results and Model Comparisons

The regression results for the regional equations for the three forecast horizons included different combinations of independent variables. Sea surface temperature and pressure indices were significant in all but 3 of the 25 equations. Drought was significant in 15 of the equations, and lagged costs were significant in only 3 equations. Six of the equations included a dummy variable to account for known accounting adjustments. Only four of the equations did not include a trend variable.

The jackknife forecast values for the regression models are shown in Figures 1, 2, and 3 for the 1-, 2- and 3-year-ahead mod-

Table 1. Forecasts of wildfire suppression expenditures for FY 2008, 2009, and 2010 made in November of 2007 using the regression models.

	Forecasted expenditures by FY (millions of 2004 dollars)		
	2008	2009	2010
Point forecast[a]	1,007	1,044	895
Mean forecast[b]	1,027	1,387	1,316
Median forecast[b]	1,019	1,284	1,162
95% confidence interval[c]			
Lower bound	786	618	478
Upper bound	1,321	2,772	3,027
90% confidence interval[c]			
Lower bound	820	692	550
Upper bound	1,261	2,431	2,588

[a] Point forecasts are made by multiplying the coefficient estimates by the right-hand-side variables.
[b] Mean and median forecasts are the mean and median of the simulated forecasts.
[c] Confidence intervals are the statistical probability that the actual expenditures will fall between the lower and upper bounds.

els, respectively. These figures also show the actual expenditures made each year and the 10-year moving average of costs for that horizon. The start date for each of these figures corresponds with the 1st year the corresponding 10-year moving average of costs is available.

The regression forecasts of expenditures for FY 2008, 2009, and 2010 are shown in Table 1. This table also includes the means, medians, and 90 and 95% confidence intervals derived from the distributions developed through the simulations. As the figures illustrate, the regression forecasts follow the actual expenditures better than the 10-year moving average of costs. The confidence intervals around the mean values of the forecasts expand as the forecast horizon increases; in other words, there is a 95% confidence interval of $2,549 million ($478 to 3,027 million) for the 3-year-ahead regression model, but an interval of only $535 million for the 1-year-ahead regression model. These results hold for all time horizons and for both the regression and the 10-year moving average models (Table 1).

In fall of 2007, the forecast of FY 2008 suppression expenditures from the 1-year-ahead model was $1.151 billion (in 2008 dollars). The actual suppression expenditures for FY 2008, which compare with the forecasts discussed in this article, were $1.163 billion. Thus, our forecast of FY 2008 suppression expenditures was lower than actual by $12 million. [1]

The forecast distribution as described previously for one set of forecasts provides some information about the relative accuracy of the different forecast models. However, to more precisely compare the accuracy of the different models, we need to compare this accuracy across many years. To do this, we calculated the root mean square error (RMSE) of the forecasts from the regression models and the 10-year moving average model. To calculate the error for each year, we subtracted the 10-year moving average forecast and the 1-, 2- and 3-year-ahead forecasts for each forecasted year from the actual expenditures for that year. The differences are squared and summed, divided by the number of observations, and the square root is computed to provide the RMSE.

Results show that the 1-year-ahead model produces a forecast with an error rate that is 60% smaller than that derived from the 10-year moving average of costs (Table 2; Figure 4). The RMSE for the 1-year-ahead regression model is $145 million,
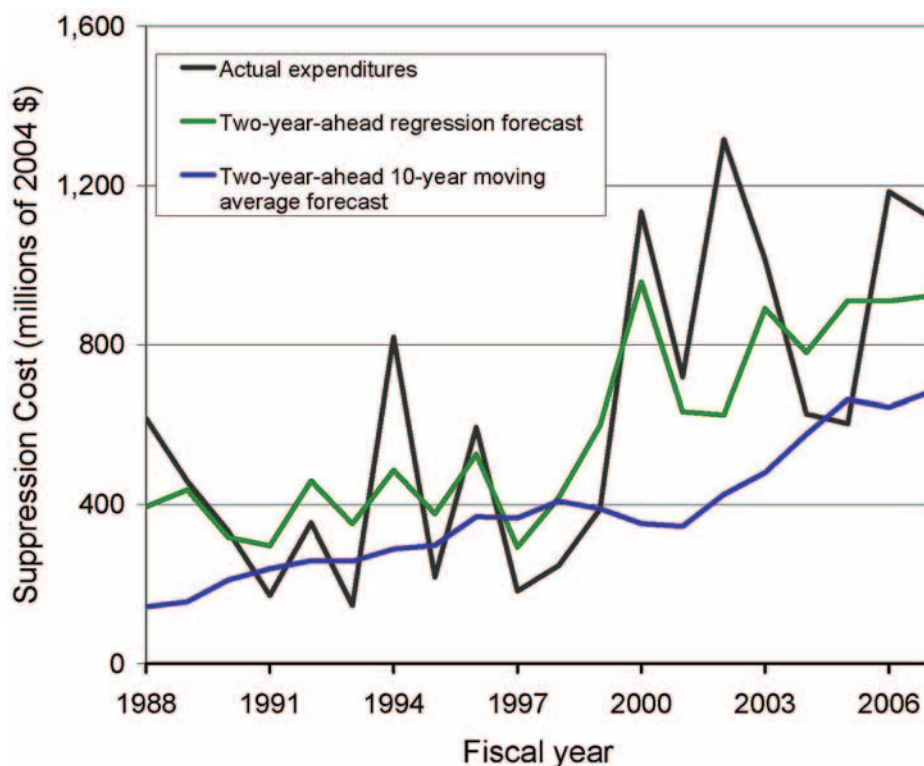

Figure 2. Comparison of actual expenditures to 2-year-ahead forecasts from the regression model and the 10-year moving average model for FY 1988–2007.
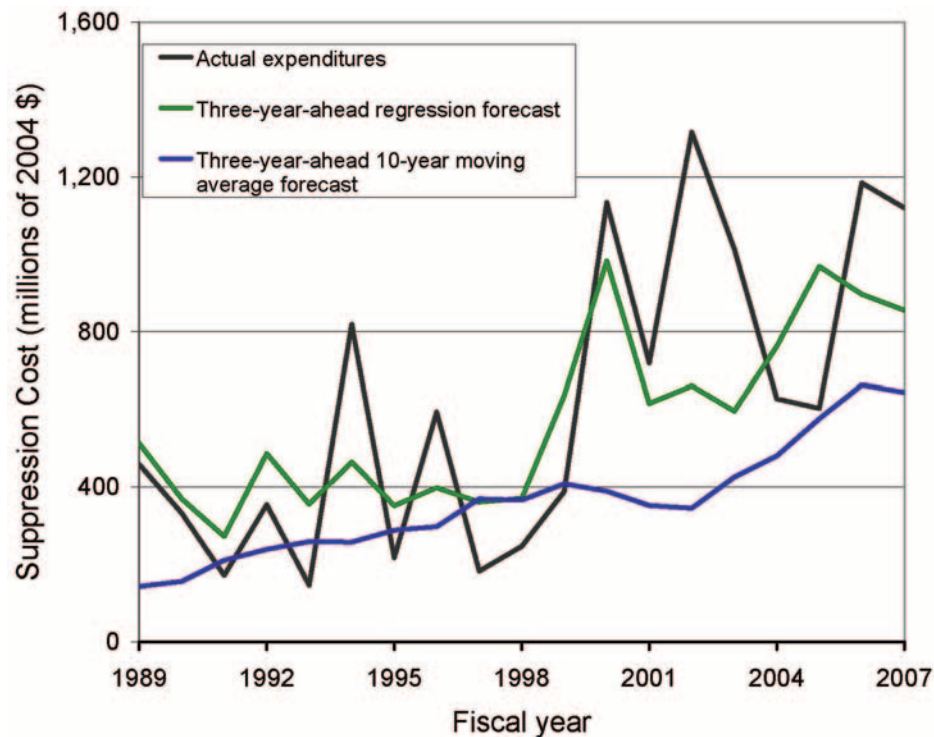

Figure 3. Comparison of actual expenditures to 3-year-ahead forecasts from the regression model and the 10-year moving average for FY 1989–2007.

compared with $369 million for the 10-year moving average. The 2- and 3-year-ahead forecast RMSEs are 40 and 35% smaller

than the 10-year moving average, respectively.

We also used the RMSE to illustrate

Table 2. Statistical forecast errors (RMSE) for the regression and 10-year moving average forecast models of wildfire suppression expenditures for 1-, 2-, and 3-years ahead.

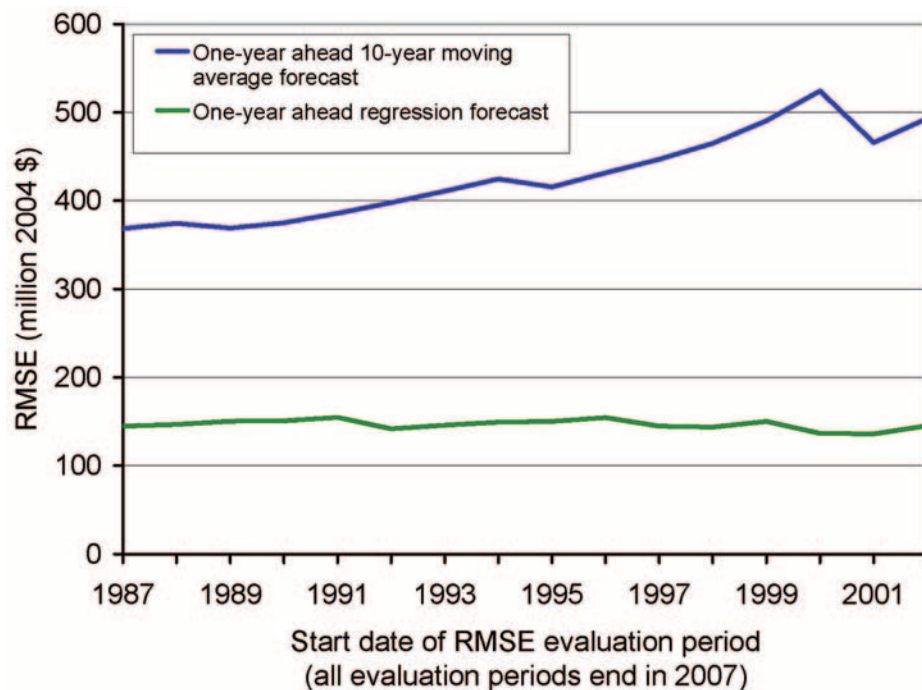|	RMSE years ahead (millions of 2004 dollars)		
	1	2	3
Regression model	145	238	265
10-yr moving average	369	397	410

Figure 4. Comparison of RMSE for the 1-year-ahead regression and 10-year moving average forecast models by forecast period length, under shortening time span windows, starting at FY 1987 (the RMSE over the period FY 1987–2007) and ending at FY 2002 (the RMSE over the period FY 2002–2007).

how the 10-year moving average forecast has deteriorated over time. This was done by calculating the average size of forecast errors, measured by the RMSE, as years progress (Figure 4). The values in Figure 4 are the RMSEs for the 1-year-ahead model calculated between the year indicated in the horizontal axis of the figure and 2007, starting in 1987 (the 1st year both forecasts are available) and ending in 2002. For example, the year 1997 on the horizontal axis represents the RMSE for FY 1997–2007. The regression forecast RMSE has a stable forecast error, around $140 million, for all subsets of the period 1987–2007. The 10-year moving average forecast, however, displays an increasing forecast error, especially since 1999, with the error ranging from the low of $369 million for the FY 1987–2007 period to a high of $524 million for the FY 2000–2007 period.

Conclusions

Suppression costs and the methods by which suppression operations are funded have placed unusual pressures on the budgets for fire management and other operations of land-managing agencies in the United States. To improve US Forest Service managers' abilities to respond to the uncertainties of future fire seasons, we developed multiequation regression models that can forecast costs with greater accuracy than simple moving average models. These regression models are significantly more accurate at all forecast time horizons that we examined. The recent increase in error associated with using the 10-year moving average of costs shows a weakness of this model, which is the slow response to changes in wildfire conditions. The more sophisticated regression models reported here are better able to capture changes in these conditions because more information regarding physical, biological, and managerial environments can be used.

In contrast, although these models produce more accurate forecasts, the 10-year moving average model has the advantage of providing year-to-year forecast stability using a familiar, transparent, and easy-to-explain method. Use of the regression models would produce a more volatile guide for agency managers when developing budgets. Although these forecasts would be more accurate, it is not clear how either agencies or Congress would accommodate more volatile budget requests under the current appropriations system. Changes in how suppression activities are funded, variations of which have been proposed in recent years, could be one way to accommodate such variability in requests.

The costs of fire suppression are increasing over time, and we have developed forecast models that attempt to account for many of the factors leading to these increased costs. Future research could examine more spatially explicit models, which would allow inclusion of explicit hazardous forest fuel, population, development, and local weather effects. More accurate statistical models, such as the ones developed here, can also serve as early warnings for likely future budget shortfalls, emphasizing the need for official mechanisms to accommodate variable funding in the future.

Endnotes

[1] In addition to our forecast, an estimate of additional wildfire management expenses was made by Fire and Aviation Management, US Forest Service ($0.296 billion), which resulted in a total forecast for FY 2008 of $1.447 billion. Total US Forest Service wildfire management expenditures for 2008 (suppression plus additional) were $1.459 billion.

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