Suppression Cost Forecasts in Advance of Wildfire Seasons

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Abstract: Approaches for forecasting wildfire suppression costs in advance of a wildfire season are demonstrated for two lead times: fall and spring of the current fiscal year (Oct. 1–Sept. 30). Model functional forms are derived from aggregate expressions of a least cost plus net value change model. Empirical estimates of these models are used to generate advance-of-season forecasts. Cost forecasts involve estimation of suppression cost equations by geographical region based on a time series of historical data (1977–2006) of costs, a time trend, and climate variables, forecasts of the next season's suppression costs, by region and in total across all regions, and generation of suppression cost forecast probability distributions by region and in aggregate. The forecasts are also evaluated historically for their goodness of fit using cross-validation techniques. The two lead time forecast models are compared with the 10-year moving average of suppression costs, currently used as a budget request formula by the US Forest Service. Results show that the spring forecast of suppression costs is statistically no better than the fall forecast for predicting the coming season's costs. However, both the spring and fall forecasts significantly outperform the 10-year moving average, reducing forecast errors by approximately 60%. FOR. SCI. 54(4):381–396.

Keywords: US Forest Service, budget, firefighting, seemingly unrelated regression, time series, suppression cost

OVER THE PAST TWO DECADES, the US federal government has experienced significant rises in the costs of suppressing wildfires on federally managed and adjacent lands (Figure 1) [1]. This rise has resulted from increases in acres burned (an output effect), as well as from increases in suppression costs per acre (an input price effect). The increase in acres burned on US Forest Service (USFS)-managed lands has occurred even as the number of reported fires has trended downward, in aggregate. Increases in acres burned have been attributed to the accumulation of fuels with past fire suppression (Arno and Brown 1991) and earlier and longer fire seasons associated with recent warming (e.g., Westerling et al. 2006). Some of the climatic patterns associated with greater fire activity may be associated with decadal-to-multidecadal variations in ocean-atmosphere interactions that may or may not be related to global change (Collins et al. 2006, Kitzberger et al. 2007). Increases in suppression costs per acre have been attributed to both an increased demand for structural protection (Snyder 1999) and rising costs of various inputs (e.g., energy, capital, labor, and contracting costs) as well as institutional constraints and requirements (Canton-Thompson et al. 2006).

Current forecasts of suppression costs (Gebert and Schuster 1999) are short-run, monthly models, designed for use during the fire season. Some models of wildfire season severity have been developed for the western part of the United States (e.g., Westerling et al. 2002, 2003), which are used as an early warning for fire management agencies of the expected extent of activity for the coming fire season, but the forecasts are unbounded. Needed are long-lead suppression cost forecasts that are made in the form of forecast probability distributions, which can provide a better picture of expected costs and the likelihoods of unusually active (and expensive) fire seasons both regionally and nationwide.

Hence, to be most useful, suppression cost forecasts should be made at operationally useful spatial and temporal scales. From a science and policy standpoint, ideally, these should also account for trends in costs that might be linked to demographic changes and climate shifts, account for the inherent uncertainty associated with forecasts, and have a model structure that is theoretically consistent.

This article describes a method to forecast suppression costs that can be used by the USFS to monitor suppression costs and plan for possible budgetary shortfalls. We report suppression cost forecasts by USFS region and in aggregate for the US federal fiscal year, October–September. These forecasts are made for two different planning horizons: first, in October of the current fiscal year, and, second, in April of the current fiscal year. Forecasts in October are needed to provide agencies and Congress with an overall budget outlook, so that steps can be taken to allocate spending well in advance of the fire season. Forecasts provided in April, which use the latest climate and drought information, may be more useful for resource prepositioning, contracting, allocating resources across regions in advance of the fire season, and planning for possible funding shortfalls. These forecasts also provide the likelihood of deficits or surpluses, given the current year's budget allocation for suppression. Model estimation has additional benefits, including quantification of aggregate cost trends by region after accounting for the importance of climatic cost shifters.

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Acknowledgments: We thank the following individuals for their helpful comments in the development of this research: Robert G. Haight, USFS Northern Research Station, St. Paul, MN; and Julio Betancourt, US Geological Survey and the University of Arizona, Tucson, AZ. In addition, the research has benefited from comments from William Breedlove and Kent Connaughton, both of Fire and Aviation Management, State and Private Forestry, USFS, in Washington, DC.

Manuscript received June 18, 2007, accepted January 29, 2008

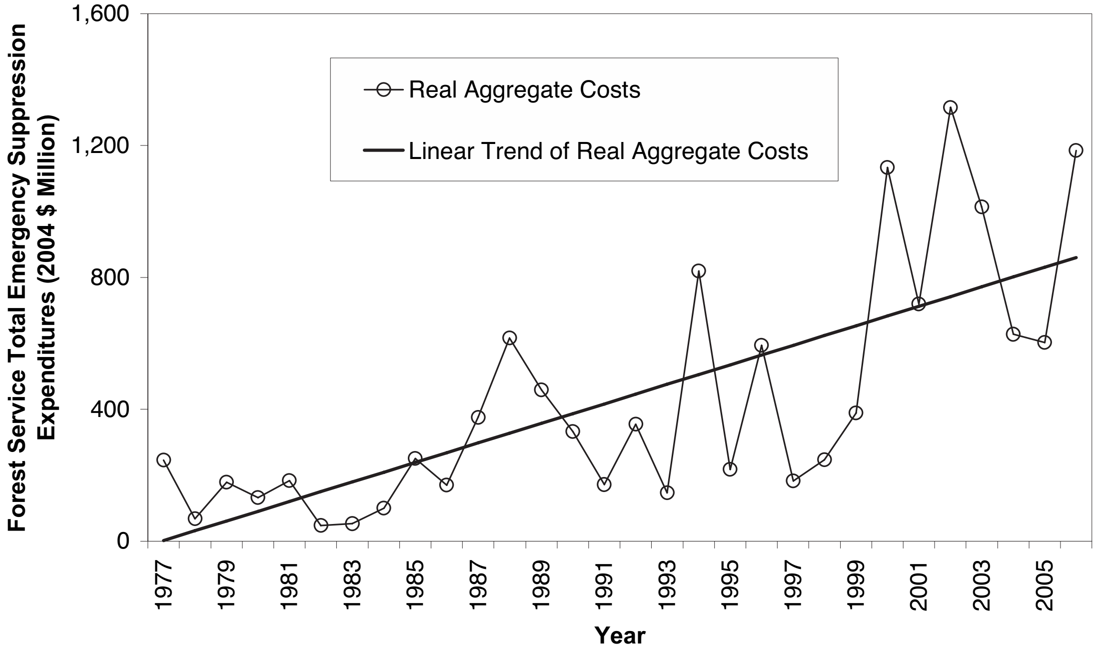

Figure 1. USFS suppression spending, 1977–2006, with a linear trend line, in fiscal year 2004 dollars.

Methods

Theoretical Structure

Research dating back to at least Headly (1916) and Sparhawk (1925) and then updated by, for example, Davis (1965), Gamache (1969), Gorte and Gorte (1979), Rideout and Omi (1990), and Donovan and Rideout (2003) expresses the agency's spending decision as a minimization of the sum of costs plus losses, which is the costs of fire management (usually fire suppression and other spending) plus losses (net value changes, possibly including discounting) from wildfires. This structure has received widespread acceptance in the resource economics community, although recent authors have sought to align the problem to account for the trade-offs among many kinds of fire management inputs (e.g., Rideout and Omi 1990, Donovan and Rideout 2003, Mercer et al. 2007).

For a land management agency whose budgets for individual activities such as fire suppression, fuels management, and output production (e.g., timber, recreation, forage, etc.) are set separately, i.e., are separable in an economic context, the least cost plus net value change (LCNVC) approach could be considered a valid approach to allocating resource inputs in the production of "protection" (see Appendix). No allowance is made for the tradeoff between inputs used in producing valuable outputs from the land that the agency manages. Nonetheless, the model characterizes the decision set of relevance for understanding the forces influencing suppression costs. We therefore developed an empirical model based on LCNVC to explain and predict annual suppression costs at the agency level.

We assume that the agency seeks to minimize the expected sum of all fire program activity spending across all planning regions and the losses of values (attributes) at risk—people, property, and natural resources—from realized wildfire activity in the current year in those same regions [min E(LCNVC)] (details of this theoretical structure is provided in the Appendix):

$$\min_x \mathrm{E}(\mathrm{LCNVC}_t) = \mathbf{R}_t'\mathbf{X}_t + \mathbf{P}_t'\mathrm{E}(\mathbf{W}_t) :$$
$$\mathbf{W}_t = W(\mathbf{Z}_t, \mathbf{X}_t) + \boldsymbol{\varepsilon}_t \,. \quad (1)$$

For each year, **X** represent fire program inputs (suppression, prevention, presuppression, and fuel treatment), **R** represent prices for the program inputs, **W** are acres burned, **P** are the net values per unit of the attributes at risk, **Z** are exogenous (free) inputs (such as weather, climate, and ecoregion attributes), and $\boldsymbol{\varepsilon}$ are random errors.

The result of solving the minimization found in Equation 1 is a cost function, expressing costs as a function of all input prices (**R**), attributes at risk prices (**P**), and exogenous inputs (**Z**) to wildfires, with expected signs of variables included:

$$\mathrm{LCNVC}_t = c\{\mathbf{R}_t(+), \mathbf{P}_t(+), \mathbf{Z}_t(\pm)\} + \omega_t, \quad (2)$$

where ω is a random variable with zero expected value. As the prices of inputs (**R**) into fire management in the agency increase, total costs (LCNVC) are expected to increase; as unit values of the attributes at risk (**P**) increase, total costs are expected to increase; and as the levels of wildfire outputs (**W**) increase, total costs are expected to increase. If we assume that costs in each of the regions comprising the agency's total land managed are separable—i.e., there is no regional cost shifting or resource shifting and there are no wildfire activity spillovers—then Equation 2 could be estimated statistically as a system of suppression cost equations with a separate equation for each region. Note that we are making no assumptions about the potential cross-regional correlations in either the ε_n or the ω_n values. Such correlations are later exploited to improve parameter estimates in statistical modeling.

Table 1. Variables evaluated in the model selection for the spring and fall models

Variable and Explanation	Lags Used	Data Source
Niño3 Oct–Feb forecast		
The average monthly forecast value (°C), October to February of the current fiscal year, of the ENSO measure Niño3 SSTA.	0	Obtained by special request from Dr. Wanqui Wang, Research Meteorologist, NOAA
Niño3 Oct–Feb		
The average monthly value (°C), October to February of the current fiscal year, of the ENSO measure Niño3 SSTA.	−1	NOAA 2006a
Niño3 Mar–Sept		
The average monthly value (°C), March to September of the current fiscal year, of the ENSO measure Niño3 SSTA.	−1	NOAA 2006a
SOI		
Southern Oscillation Index value (standardized to be unitless), the monthly average sea level air pressure difference between Tahiti and Darwin.	February, November, August, and May of the current fiscal year	NOAA 2006b
PDO		
Pacific Decadal Oscillation index value (standardized to be unitless), the monthly average sea surface temperature anomaly observed in the Pacific Ocean, poleward of 20°N.	February, August, and May of the current and previous fiscal year and November of 2 previous fiscal years	Mantua and Hare 2007
AO		
Arctic Oscillation index value (standardized to be unitless), the monthly average sea level pressure anomaly, poleward of 20°N.	February, November, August, May of the current fiscal year; averaged for RFS equations into quarterly lags of the previous fiscal year	NOAA 2007b
NAO		
North Atlantic Oscillation index value (standardized to be unitless), the monthly average atmospheric pressure anomaly observed in the Atlantic Ocean, poleward of 20°N.	February, November, August, May of the current fiscal year	NOAA 2007a
PDSI		
Palmer Drought Severity Index (hydrological), averaged across all crop reporting districts found in national forests in USFS Regions 1–6, weighted by each national forest's area.	March of the current and previous fiscal year	NOAA 2006c
PDSI WtdZ		
The Palmer Z-index of soil moisture, standardized to index departures from monthly long-term normal values; for each region, it is weighted by the area of national forest found in each crop reporting district of the region.	March, June, and September of the previous fiscal year and December of the previous and current fiscal year; regions evaluated are 1, 2, 3, 4, 5, 6, 8, 9, and 10	NOAA 2006c

Empirical Approach

Our theoretical structure makes no assumptions about the functional forms required by our empirical models. In a forecasting model, a suppression cost function for a region could include trend variables replacing both input prices and unit values at risk. Additionally, research has shown that wildfire activity measures may not be normally distributed (e.g., Moritz 1997, Li et al. 1999, Schoenberg et al. 2003), and policy and scientific analysts have pointed out that large wildfires comprise the vast majority of area burned by fires (and therefore spending) by the USFS (Alvarado et al. 1998, Malamud et al. 2005). For example, fire suppression expenditures are concentrated on large fire events; the largest 1% of fires apparently consumes 60% of all suppression funds (Strategic Issues Panel on Fire Suppression Costs 2004). Research by Strauss et al. (1989) also shows that 80–90% of wildfire area burned in the western United States is attributable to 1% of the fires occurring there and that the fires are distributed non-normally (e.g., Pareto or log normal) in size-frequency space. The cost per unit area burned usually decreases with the size of the fire (e.g., Strategic Issues Panel on Fire Suppression Costs 2004). Although it is not clear that extreme value or logarithmic fire size-frequency distributions naturally would lead to regional annual suppression cost non-normality, given this possibility we allow for the possibility that regional annual suppression cost totals are either normally or log normally distributed and test the estimated residuals for normality.

Forecasting Models

Theoretical and derived empirical models such as the one described above are not always amenable to forecasting because some variables that our theory requires to be included are not always available to the analyst at the time of forecasting. In their place we often insert proxies or instruments for those unavailable variables. In forecasting, as forecast lead time increases, the use of proxies or instruments often increases. Our empirical approach to forecasting suppression costs contends with this, as well. We contemplate two forecasts, $\mathbf{C}_t^{\text{fall}}$ and $\mathbf{C}_t^{\text{spring}}$, where $\mathbf{C}_t^{\bullet}$ is an $N \times 1$ vector of the costs of N regions, as forecast using data available in either the fall or in the spring of the current federal fiscal year (hereafter, "fall" and "spring," respectively). The cost models in the two periods have some common right-hand side variables. The data used in both models require time series of cost observations for each year (identical left-hand side variables), a time trend, and exogenous variable observations. If we have a time series of such data for multiple locations, then a natural estimator would be one that exploits potential correlations across the N locations where suppression is being conducted and spending is occurring. Rewrite Equation 2 as

$$\mathbf{C}_t^{\bullet} = \mathrm{C}(\mathbf{R}_t^{\bullet}, \mathbf{P}_t^{\bullet}, Z_t^{\bullet}), \tag{3}$$

where the symbol $(\cdot)$ represents fall or spring, $\mathbf{C}_t^{\bullet} = (C_{1,t}^{\bullet}, C_{2,t}^{\bullet}, \ldots, C_{N,t}^{\bullet})$, $\mathbf{R}_t^{\bullet} = (\mathbf{r}_{1,t}^{\bullet}, \mathbf{r}_{2,t}^{\bullet}, \ldots, \mathbf{r}_{N,t}^{\bullet})$, $\mathbf{P}_t^{\bullet} = (\mathbf{p}_{1,t}^{\bullet}, \mathbf{p}_{2,t}^{\bullet}, \ldots, \mathbf{p}_{N,t}^{\bullet})$, and $Z_t^{\bullet} = (z_{1,t}^{\bullet}, z_{2,t}^{\bullet}, \ldots, z_{N,t}^{\bullet})$. In empirical estimation, we account for any potential cross-equation error correlations in regional costs owing to factors linked to an error correction process, as

$$\mathbf{C}_t^{\bullet} = \mathbf{Y}_t^{\bullet\prime}\boldsymbol{\beta} + \boldsymbol{\omega}_t^{\bullet} \quad \omega_{n,t}^{\bullet} = e_{n,t}^{\bullet} + \rho^{\bullet}\omega_{n,t-1}^{\bullet}. \tag{4}$$

This error correction process could derive from regional cost sharing. Detailed accounting analyses by the authors have identified significant cost-shifting among USFS regions: fire expenditures in one region may be credited to another region. (We term this the "by region-for region" issue.) In empirical modeling, fire activity in one region could, therefore, be correlated with costs in other regions. A system approach to estimation would, therefore, produce smaller standard errors of parameter estimates because equation errors would be more highly correlated. The effects of this accounting phenomenon on observed regional costs could also be minimized by combining regions most likely to share costs. In our models, we have done this by aggregating some regions in the system cost modeling and by including the drought measures of other regions in the cost model of a particular region (e.g., Westerling et al. 2002, 2003). Regional aggregation carries with it new problems (aggregation bias), but this should reduce the problems associated with regional cost sharing if many of the variables driving costs in each region are common to all in the regional aggregate. We do not aggregate all regions into one agencywide cost model because evidence shows that fires and costs in each are driven by different factors. Therefore, the by region-for region issue remaining in our models may lead to an unknown degree of parameter estimation biases and inconsistencies that could reduce equation goodness of fit and out-of-sample forecast accuracy.

Equation 4 can be estimated using generalized least squares (GLS) as a seemingly unrelated regression (SUR) model, where $\mathbf{Y}_t^{\bullet} = (\mathbf{y}_{1,t}^{\bullet}, \mathbf{y}_{2,t}^{\bullet}, \ldots, \mathbf{y}_{N,t}^{\bullet})$ and $\mathbf{y}_{n,t}^{\bullet} = (\mathbf{r}_{n,t}^{\bullet}, \mathbf{p}_{n,t}^{\bullet}, \hat{w}_{n,t}^{\bullet})$. Dwivedi and Srivastava (1978) showed that the more correlated are the disturbances ($\omega_{n,t}^{\bullet}\omega_{q,t}^{\bullet}$, $n \neq q$), the greater the efficiency gain of GLS compared with single-equation ordinary least squares (OLS) and that the less correlated are the individual $\mathbf{y}_{n,t}^{\bullet}$ in $\mathbf{Y}_t^{\bullet}$, the greater the efficiency gain compared with single-equation OLS. It is likely that weather and climate shocks, random factors not fully captured by the variables included in $\mathbf{Y}_t^{\bullet}$ (e.g., droughts or rainy periods not adequately explained by variables used to forecast costs) have some correlations across regions in the United States, so we would expect some gain of SUR over single-equation OLS. Many of the variables representing the columns of $\mathbf{y}_{n,t}^{\bullet}$ and $\mathbf{y}_{q,t}^{\bullet}$ $(n \neq q)$ will differ because of differing lagged values of the dependent variables, which are potential elements in Equation 4.

Hypotheses and Explanatory Variables

Our empirical versions of the regional cost equations for fall and spring are based on ocean temperatures, sea level pressure, drought indices, past regional costs, and time trends. Ocean temperatures have been shown to be related to fire activity in many regions of the United States (e.g., Simard et al. 1985, Swetnam and Betancourt 1990, Brenner 1991, Gedalof et al. 2005, Collins et al. 2006, Kitzberger et al. 2007). Although area burned is positively and highly correlated with realized costs, our method does not forecast area burned. Instead, costs are related directly to hypothesized variables as shown in Table 1. These variables are described in more detail in the Appendix. Inclusion of variables in the full (most general) statistical models was based on a simple inspection of the correlation matrix between suppression costs and the possible variables, including variables with the highest correlations ($\rho > 0.30$) with costs. Once these correlates were identified, individual region or regional aggregate equations were estimated with ordinary least squares. We dropped the variables with t values <1.5, and then, after reestimation of the equation with the shorter set, further dropped those with t values <1.5 again. Then, these "final" equations were estimated jointly in a SUR model [2].

Suppression cost data are based on USFS accounting databases as compiled by the USFS Rocky Mountain Research Station. These data were available beginning in 1977 for the nine land management regions, as well as the for the

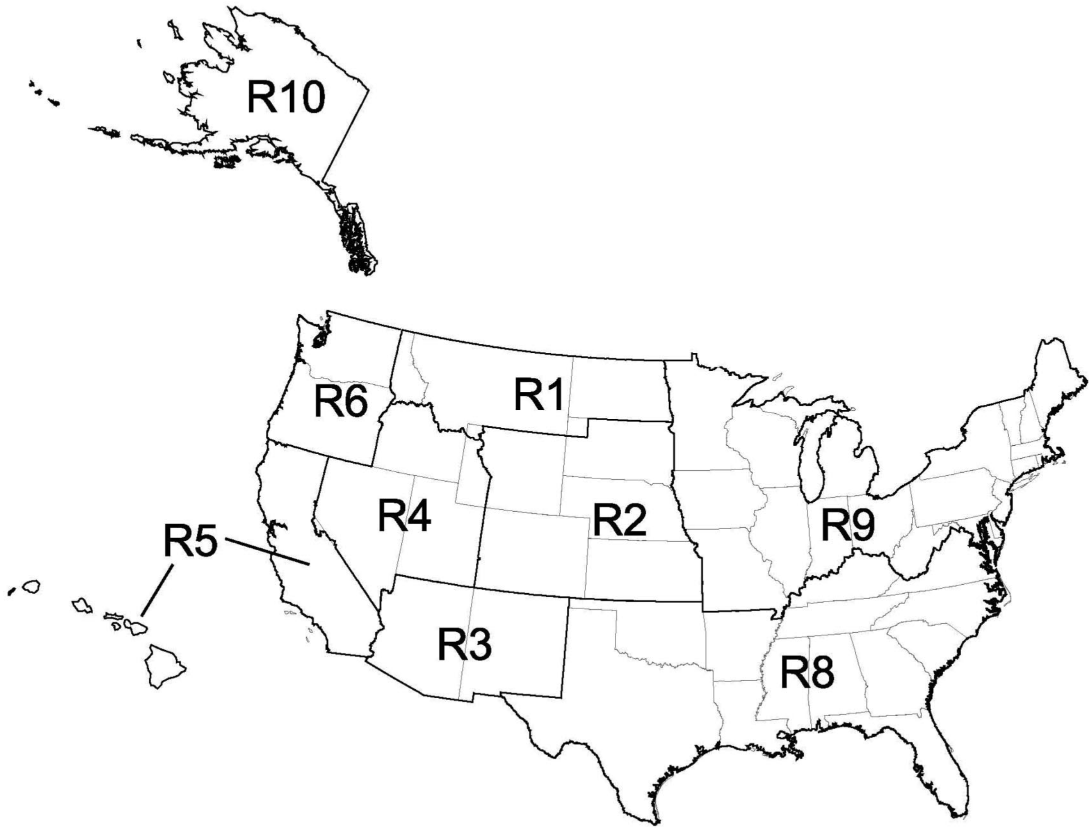

Figure 2. Map of USFS regions.

rest of the Forest Service (RFS), which includes the national offices, research stations and the National Interagency Fire Center expenditures related to USFS fires. Wildfire suppression expenditures include all costs incurred by the USFS and not reimbursed by other agencies for suppressing wildfires including salaries, contracts, equipment, and supplies.

We deflate costs by the annual average US gross domestic product deflator for each fiscal year (October–September) (US Department of Commerce 2006) to make an entire time series, $t = 1, \ldots, T$, comparable in dollar terms. Once the dependent variable shown in Equation 4 is deflated, real changes in input costs (e.g., wages), in addition to technology changes and changes in the values at risk (the quantity and unit values of attributes at risk) are assumed to be consistently modeled by a time index. This time index is highly correlated with indices of producer prices for capital, labor, and energy in the United States, which are also correlated with each other; inclusion of both a trend and each of those price indices would introduce multicollinearity.

In the empirical estimate of Equation 4, spatial aggregates (Figure 2) are USFS Regions 1–6 ("Western Aggregate") [3], Region 8 (Southern Region), Region 9 (Eastern Region), Region 10 (Alaska), and RFS. In the spring model, the costs of regions 8 and 9 are combined into a single aggregate to address problems of important non-normalities in residual series in initial estimates of suppression cost equations for these two regions and also to further mitigate the by region–for region cost-sharing issue mentioned earlier [4].

Forecasts

Once empirical estimates of Equation 4 are obtained using SUR methods, forecasts of suppression costs by USFS region or region aggregates are made at the two alternative lead times, using climate data available at that time. As Westerling (2003) showed, although season forecasts depend on lags of drought indices extending back to 2 years, fire season activity is related to winter precipitation of the current fiscal year in some locations. Given this, we expect that the spring estimator will perform better than the fall.

Assessing Forecast Accuracy

We calculated goodness-of-fit statistics for each forecast lead time based on the leave-one-out cross-validation approach to out-of-sample predictions of suppression costs, by region [5]. These statistics include the mean absolute percent error (MAPE), the root mean square error (RMSE), and the percent correct direction of change prediction. For the first two, a value of zero implies a perfect forecast. A 100% correct prediction of direction change does not imply a perfect forecast but may be helpful in some decisionmaking.

Results and Discussion

Variables evaluated in the process of model selection are tallied in Table 1. This table also lists the abbreviations used in reporting the model estimates for fall (Table 2) and spring (Table 3) models. The models selected explained between

Table 2. Fall USFS suppression cost forecast model regression results, FY 1977–2006

Model and Variable	Coefficient	SE	t Statistic	Probability
Western aggregate (Regions 1–6)				
Constant	−33,962,907,371	4,814,014,106	−7.055	0.000
Niño3 Oct–Feb forecast	−356,165,877	34,543,954	−10.311	0.000
Niño3 Oct–Feb (−1)	−245,786,128	31,200,252	−7.878	0.000
Niño3 Mar–Sept (−1)	376,933,278	58,527,090	6.440	0.000
SOI Aug (−1)	−140,373,673	21,828,706	−6.431	0.000
PDO May (−1)	−209,266,230	26,625,883	−7.860	0.000
PDO Feb (−1)	343,118,240	45,444,661	7.550	0.000
PDO Nov (−2)	−96,237,847	19,293,385	−4.988	0.000
AO May (−1)	−89,739,968	25,715,049	−3.490	0.001
March PDSI (−1)	−81,170,535	10,990,553	−7.385	0.000
NAO Feb (−1)	40,999,854	29,145,826	1.407	0.163
Year	17,120,647	2,417,770	7.081	0.000
Log(Southern Region)				
Constant	−1,143.647	195.891	−5.838	0.000
PDSI R3 Jun-WtdZ (−1)	0.154	0.071	2.159	0.033
PDSI R3 Mar-WtdZ (−1)	−0.169	0.078	−2.182	0.031
Log(Year)	152.730	25.786	5.923	0.000
Log(Eastern Region)				
Constant	−151.184	24.153	−6.259	0.000
Niño3 Mar–Sept (−1)	−0.519	0.166	−3.136	0.002
SOI Aug (−1)	−0.343	0.078	−4.414	0.000
PDSI R9 Sep-WtdZ (−1)	−0.203	0.084	−2.426	0.017
PDSI R8 Jun-WtdZ (−1)	−0.254	0.070	−3.603	0.000
PDSI R1 Jun-Wtd Z (−1)	−0.164	0.061	−2.665	0.009
PDSI R2 Jun-WtdZ (−1)	0.320	0.060	5.322	0.000
Year	0.084	0.012	6.888	0.000
Alaska Region				
Constant	2,042,330	398,071	5.131	0.000
Niño3 Oct–Feb Forecast	−2,803,838	461,053	−6.081	0.000
Niño3 Mar–Sept (−1)	2,717,087	866,049	3.137	0.002
Niño3 Oct–Feb (−1)	−2,207,621	483,647	−4.565	0.000
SOI May (−1)	−892,290	306,050	−2.916	0.004
AO Aug (−1)	−1,750,467	713,336	−2.454	0.016
RFS				
Constant	−9,589,948,333	1,878,366,134	−5.105	0.000
Cost RFS (−3)	−0.367	0.128	−2.865	0.005
Niño3 Mar–Sept (−1)	−16,844,475	9,087,753	−1.854	0.067
AO Aug (−1)	−18,017,918	11,386,841	−1.582	0.117
Year	4,852,924	944,157	5.140	0.000
PDSI R5 Sep-WtdZ (−1)	8,780,926	5,967,640	1.471	0.144
PDSI R6 Sep-WtdZ (−1)	−20,679,469	6,413,411	−3.224	0.002
AO Apr-Jun (−1)	−51,895,069	16,008,360	−3.242	0.002

60 and 94% of the variation in the 31 years of data (Table 4). The models for spring had higher individual R^2 values than the fall models, and spring and fall had a significantly lower RMSE than the 10-year moving average (Table 5). There was, however, no significant difference between the RMSE of the fall and spring forecasts, implying that the additional climate information available in the spring, although useful, is not different enough from the data available in the fall to make large changes in forecast confidence. Normality tests of individual equation residuals in each system indicate that none of the four equation residual series of the spring model tested as non-normal using the Jarque-Bera normality test. In the fall model, two of the residual series of the five equations tested as being distributed non-normally: Region 8 ($P = 0.03$, due to slight leptokurtosis and negative skew) and the RFS aggregate ($P = 0.01$, due to leptokurtosis and positive skew). Considered together, the limited number of observations leads us to conclude that these rejections could be purely by chance. The high explanatory power of the models also leads us to judge that this degree of non-normality is not important enough to create significant problems in the forecast of aggregate costs—not least because of their individual small contribution to total costs and the fact that their opposite skewness would tend to partially cancel out when an agencywide forecast is made. Further, it bears considering that the ultimate measure of accuracy of these models comes in forecasting, and in-sample statistics may not be highly relevant to making forward-looking predictions.

Fall Forecasts

The fall modeling system uses linear models for Regions 1–6, Region 10, and the RFS and log models for Regions 8 and 9. An average of 80% of USFS suppression expenditures are in Regions 1–6; fortunately for modeling and forecasting purposes, this model is also the best fitting, with an R^2 of 0.93. Ten climate variables and the time trend are

Table 3. Spring USFS suppression cost forecast model regression results, FY 1977–2006

Model and Variable	Coefficient	SE	t Statistic	Probability
Western Aggregate (Regions 1–6)				
Constant	−31,994,525,285	4,571,188,234	−6.999	0.000
Year	16,159,159	2,295,693	7.039	0.000
SOI Nov (−1)	37,557,720	15,404,995	2.438	0.017
Niño3 Oct–Feb (−1)	−218,158,157	31,411,311	−6.945	0.000
Niño3 Oct–Feb forecast	−293,427,991	35,609,010	−8.240	0.000
Niño3 Mar–Sept (−1)	330,944,881	57,703,490	5.735	0.000
SOI Aug (−1)	−140,865,223	20,649,115	−6.822	0.000
PDO May (−1)	−188,208,664	23,327,375	−8.068	0.000
PDO Feb (−1)	289,475,542	32,750,994	8.839	0.000
PDO Nov (−2)	−87,460,756	17,195,521	−5.086	0.000
March PDSI (−1)	−73,394,088	10,909,789	−6.727	0.000
AO May (−1)	−84,850,056	23,860,228	−3.556	0.001
Log(Southern and Eastern Regions)				
Constant	−987.165	141.785	−6.962	0.000
Log(year)	132.139	18.665	7.080	0.000
PDSI R2 Jun Wtd Z (−1)	0.105	0.043	2.445	0.017
SOI Aug (−1)	−0.334	0.072	−4.623	0.000
SOI Nov (−1)	0.239	0.066	3.603	0.001
PDSI R8 Dec Wtd Z (−1)	−0.304	0.076	−3.992	0.000
Log(Alaska Region)				
Constant	−1,078.694	373.482	−2.888	0.005
Dummy variable − 1999	−5.701	0.796	−7.162	0.000
Log(year)	143.777	49.160	2.925	0.005
Niño3 Oct–Feb forecast	−0.776	0.152	−5.120	0.000
SOI May (−1)	−0.719	0.138	−5.218	0.000
AO Aug (−1)	−0.844	0.315	−2.678	0.009
AO Feb	0.236	0.108	2.178	0.032
AO Feb (−1)	0.444	0.108	4.120	0.000
RFS				
Constant	−7,038,941,540	1,271,874,390	−5.534	0.000
Year	3,565,146	638,712	5.582	0.000
March PDSI	−11,635,956	3,147,529	−3.697	0.000
PDSI R2 Jun Wtd Z (−1)	11,712,342	3,393,950	3.451	0.001
PDO Feb	−20,082,884	6,097,033	−3.294	0.001
AO May (−1)	−35,591,948	8,589,048	−4.144	0.000

significant, with costs increasing by $17 million per year, after accounting for climate variations. Initial models of the RFS costs indicated a significant 3-year autocorrelation of residuals; including the 3-year lagged dependent variable eliminated this statistical correlation, and this lag was retained in the final specification.

Evaluation of the climate variables is complicated by the relationships between the climate measures. For example, an El Niño event can be measured by the Niño3 Sea Surface Temperature Anomaly (SSTA) as well as by the Southern Oscillation Index (SOI). In addition, the Pacific Decadal Oscillation (PDO) is highly correlated with El Niño/Southern Oscillation (ENSO), but is on a 10- to 20-year cycle rather than a 2- to 7-year cycle. When an El Niño event occurs, the Niño3 SSTA is positive, PDO is generally positive, and SOI is negative. El Niño events are considered "warm" phases, leading to warm, dry winters in the Pacific Northwest and cool, wet winters in the Southwest. La Niña events are considered "cool" phases, with generally opposite implications for season temperature and precipitation patterns. Similarly, whereas the Palmer Drought Severity Index PDSI measures actual drought conditions, it is also related to these larger climatic disturbances, although it carries persistence that can capture longer run effects on fuels and fuel moisture important to wildfire activity.

To more fully describe the individual effects of changes in the predictors included in our models, we used comparative statics (Table 6). When doing these, we individually varied one variable while holding others constant at their sample means. These reference conditions of the included variables were the average values for the warm phases (Niño3 SSTA and PDO >0 and SOI <0) and cool phases (Niño3 SSTA and PDO <0 and SOI >0), and the coefficients from the fall model. During an El Niño event, in which both lagged and forecast values for ENSO stay in the warm phase, suppression costs are expected to be lower by $127 million. Conversely, when the systems are in the cool phase, costs are expected to be higher by $62 million. The largest variations in costs occur when there is a transition between El Niño and La Niña. When all systems are in a cool phase, but the Niño3 forecast is warm (El Niño), costs are expected to increase by $599 million. When La Niña conditions exist but the forecast is for an El Niño to emerge in the coming months of the year, then costs would be lower by $664 million.

For all of the fall equations, the effect of the Arctic Oscillation (AO) is negative, as hypothesized, and the effect

Table 4. Fall and spring USFS suppression cost forecast model evaluation statistics

	Fall Models	Spring Models
Western Aggregate (Regions 1–6)	Linear	Linear
Observations	25	25
R^2	0.931	0.942
Adjusted R^2	0.873	0.893
SE of regression	106,631,336	97,965,000
Durbin-Watson stat	2.467	2.463
Southern + Eastern Regions		Log
Observations		30
R^2		0.797
Adjusted R^2		0.755
SE of regression		0.484
Durbin-Watson stat		1.773
Southern Region	Log	
Observations	30	
R^2	0.600	
Adjusted R^2	0.554	
SE of regression	0.662	
Durbin-Watson stat	1.832	
Eastern Region	Log	
Observations	30	
R^2	0.701	
Adjusted R^2	0.606	
SE of regression	0.668	
Durbin-Watson stat	2.014	
Alaska Region	Linear	Log
Observations	25	24
R^2	0.650	0.832
Adjusted R^2	0.558	0.759
SE of regression	2,086,350	0.913
Durbin-Watson stat	1.670	2.068
Rest of FS	Linear	Linear
Observations	27	30
R^2	0.699	0.751
Adjusted R^2	0.589	0.700
SE of regression	39,284,608	33,147,040
Durbin-Watson stat	2.706	2.317

of the North Atlantic Oscillation (NAO) is positive, also as hypothesized. The PDSI measures show varying effects, depending on the model and the lag. The lagged March PDSI shows a negative effect on suppression costs for the western aggregate model, implying that costs are lower when drought is less extensive over the western United States. The effects of other PDSI measures on costs are less clear. For example, the Region 8 model uses the Region 3 March and June lagged values, implying that if drought conditions are steady in Region 3, then there will be little effect on costs, whereas if drought worsens in Region 3 between March and June, Region 8 costs will be higher. This could be because the climate in Region 3 is a leading indicator of climate in the southern region, or, just as possible, that some Region 8 resources are being used in suppressing fires in Region 3. The latter possibility illustrates the effect of the by region-for region issue alluded to earlier in this article. Similarly, the Region 9 model has the PDSIs of other regions included in its model, all of which have negative coefficients except for Region 2. Wetter conditions in the specified months in Regions 1, 8, and 9 lead to lower costs, whereas wetter conditions in Region 2 lead to higher costs, ceteris paribus.

The RFS model also includes PDSI measures. The lagged PDSI for Region 5 (California, the single most costly region in the West, comprising 37% of costs, on average) for September is positively related to costs, whereas the lagged PDSI for Region 6 (the second most costly region) for the same month is negative, implying that a September drought in California reduces costs but a September drought in the Pacific Northwest increases costs.

Spring Forecasts

The spring models are similar to the fall models, but there are some different selections of climate variables used to develop the "best" models. For the Region 1–6 aggregate, the model is very similar, dropping one climate measure (NAO) and including another (the November lagged SOI). The in-sample R^2 is slightly higher than that in the fall model's Region 1–6 aggregate model. The coefficient on year indicates that, similar to the fall model, ceteris paribus, costs for the western aggregate are rising at an average rate of more than $16 million per year. Over the span of most of the equation estimates in the spring and fall models for 1982–2006, costs have increased, ceteris paribus.

The Eastern and Southern regions were combined for spring and now include the lagged November SOI value and lagged regional PDSIs for Regions 2 and 8, and the Region 8 December value replaces the June value. Drought indices for Regions 1, 3, and 9 are dropped, as are lagged average values of the Niño3 March–September SSTA. The Region 10 model is estimated using logarithmic values for the dependent variable, necessitating inclusion of a dummy variable for 1999, a year when costs are recorded as negative. In the Region 10 specification as well, lagged Niño3 values are dropped and two new AO measures are included (current February and lagged February).

The RFS model appears to benefit most from nearer term climate data, compared with the models of other regions' models, using the current westwide March PDSI (*H*) and the current February PDO value. The Region 2 lagged June PDSI is added to this model, whereas the PDSIs for Regions 5 and 6 are dropped. Also dropped are the AO April–June measure, the Niño3 lagged March–September measure, and the 3-year lag of RFS costs. The coefficient on year indicates that costs for the RFS are rising at the rate of nearly $3.6 million per year.

System Results and Model Comparisons

Table 5 shows the system evaluation statistics for the two forecast models and the 10-year moving average for the period 1989–2006. Before the development of these models, the 10-year moving average was the best model available for use by policymakers and analysts for the USFS. Statistics in Table 5 show that the 10-year moving average is better at predicting the direction of change (94% correct predictions) than either the fall (88%) or spring (82%) models. The MAPE is higher for the 10-year moving average (49%) than either the fall (38%) or spring (35%) models. The RMSE, however, is statistically significantly higher for the 10-year moving average ($401 million) than for the fall ($173 million) or spring ($150 million) models. These

Table 5. System evaluation statistics and comparison, 1989–2006

	% correct direction of change	MAPE	RMSE (2004 $, million)	2006 forecast (2004 $, million)	2007 forecast (2004 $, million)
Fall model	88	38	173	1,046	847
Spring model	82	35	150	996	942
10-year moving average, 1989–2005	94	49	401	663	644

Table 6. Comparative statistics on the effects of El Niño-Southern Oscillation measures individual and collective effects on suppression costs in the Western Aggregate (Regions 1–6) of USFS regions

Variables	Coefficients	Warm average	Cool average	Warm value effect	Cool value effect	Change in costs
				($million)		
Individual variable effects						
Niño3 Oct–Feb forecast	−356,165,877	1.07	−0.97	−381	345	
Niño3 Oct–Feb (−1)	−245,786,128	0.98	−0.71	−241	175	
Niño3 Mar–Sept (−1)	376,933,278	0.70	−0.38	264	−143	
SOI Aug (−1)	−140,373,673	−1.80	1.23	253	−173	
PDO May (−1)	−209,266,230	1.25	−0.72	−262	151	
PDO Feb (−1)	343,118,240	0.94	−1.13	323	−388	
PDO Nov (−2)	−96,237,847	0.86	−0.99	−83	95	
Climate regimen effects						
All warm						−127
All cool						62
Niño3 SOI warm, PDO cool						−247
Niño3 SOI cool, PDO warm						182
Forecast warm, all others cool						−664
Forecast cool, all others warm						599

RMSEs for the fall and spring models, however, are not statistically significantly different from each other, despite the slightly smaller error shown for the latter. As always, when one is using a short data series, additional years of data could bring substantial improvements in modeling and forecasting. The forecast values from the three models for FY2006 and FY2007 are also shown in Table 5.

Forecast Distributions

Comparisons of forecasts to actual suppression costs (agencywide for the fall and spring) (Figures 3 and 4, respectively) demonstrate the out-of-sample predictive abilities of the fall and spring models. For these figures, back-transformations of forecast logarithmic costs were accomplished using an approach recommended by Karlberg (2000). Forecast precision is illustrated by producing a forecast probability distribution of costs for fiscal year 2007. To generate random forecast errors needed for such a probability distribution, we applied methods developed by Krinsky and Robb (1986). Details are provided in the Appendix.

The probability distribution of fiscal year 2007 costs made with the fall model shown in Figure 5 indicates the forecast mean, point estimate, and 90 and 95% confidence intervals that are consistent with a continuing overall trend of rising real costs, although the forecast is down from the actual amount spent in 2006. The 2007 budget allocation for suppression expenditures was $535 million, which, by measure of the fall model, had less than a 1% likelihood of being sufficient to cover actual expenditures. In summary, either the fall or spring forecast model represents an improvement over using the 10-year moving average for forecasting suppression costs within the current fiscal year [6].

Cost Trend Implications

Estimated coefficients on the forecast model imply that positive trends exist in costs across most regions, after accounting for climate variables included. This is true for the Region 1–6 aggregate and for other regions except for Region 10, and it is found for both fall and spring versions of our forecast models. Accurate assessment of the effects of these regional cost trends on overall costs perhaps would be best for models estimated with current (not lagged) climate variables. However, such an exercise is informative even for these forecast models to get a picture of the overall effect of rising real costs of inputs, contracts, and, potentially, fuels and increasing populations in the wildland-urban interface. To provide such information, we evaluate the net effect of the positive trends across all USFS Regions for 1982–2006 implicit in the model estimates. For both systems of equations, those shown in Table 2 (fall) and Table 3 (spring), we set the value of our time trend variable ("year") equal to 1982 across all years of the "year" variable and compared the in-sample predicted values (i.e., not the forecast values) with the in-sample predicted values when "year" rises normally. For the fall model, the effect of the time trend is an accumulated extra suppression cost of $7.1 billion for 1983–2006. The 2006 predicted cost is $488 million with year set equal to 1982, or $594 million (55%) lower than the in-sample predicted value ($1,082 million) for 2006. Likewise, the 2007 forecast value was $242 million, compared to the $847 million that we forecast in real

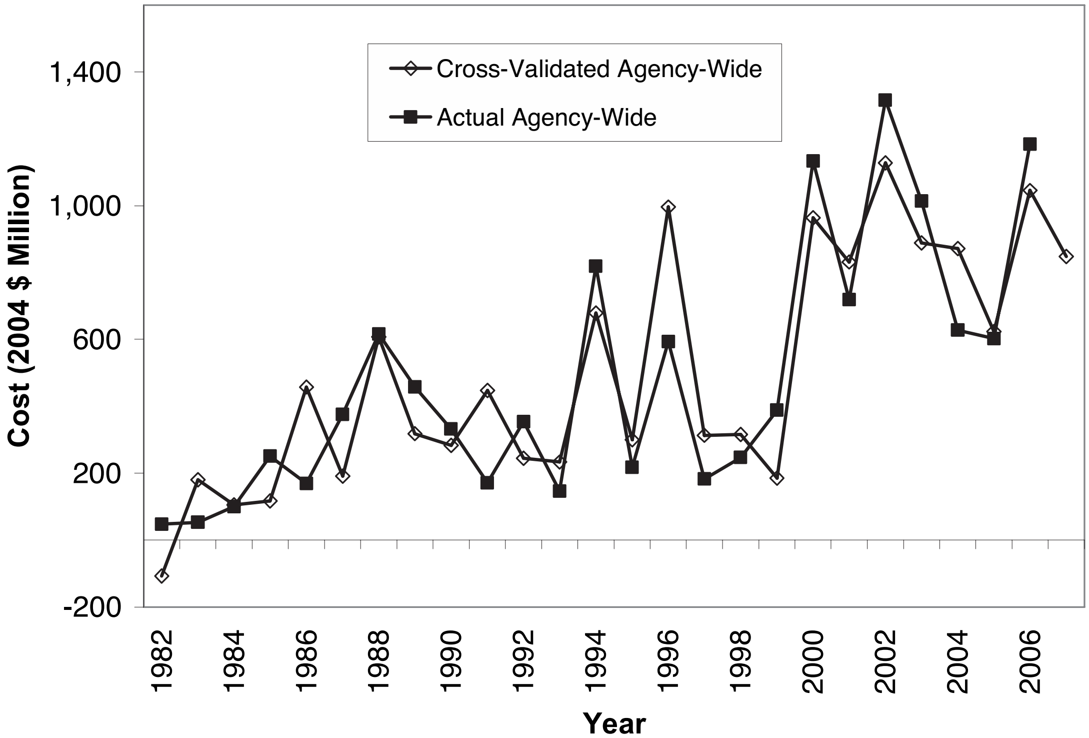

Figure 3. Cross-validated fall USFS forecasts (1982–2006), the 2007 forecast, and actual agencywide suppression costs in the USFS (1982–2006), in fiscal year 2004 dollars.

dollar terms for 2007. For the spring model, results are similar and are available from the authors. These cost differences due to the time trend are significantly different from zero, which is what would be expected, given the high significance of the trend variables in the statistical models shown in Tables 3 and 4.

Conclusions

Forecasting of suppression costs within the current fiscal year can provide information to agency administrators, as well as to Congress, regarding potential funding shortfalls for wildfire suppression in the upcoming fire season. The

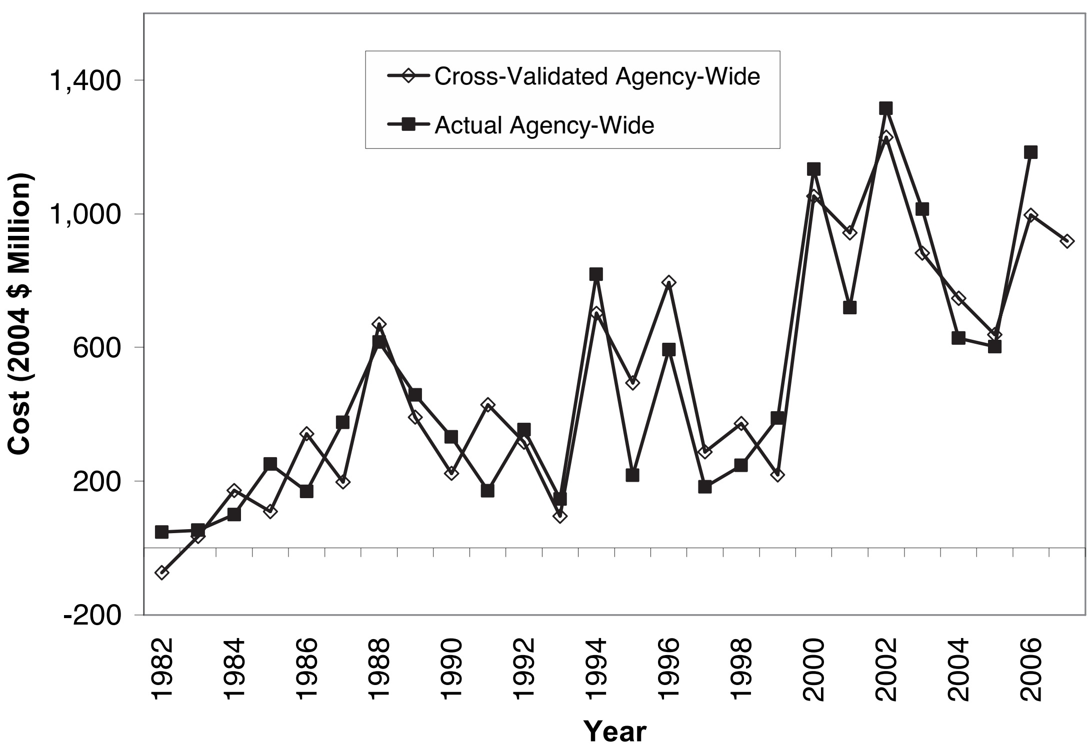

Figure 4. Cross-validated spring USFS forecasts (1982–2006), the 2007 forecast, and actual agencywide suppression costs in the USFS (1982–2006), in fiscal year 2004 dollars.

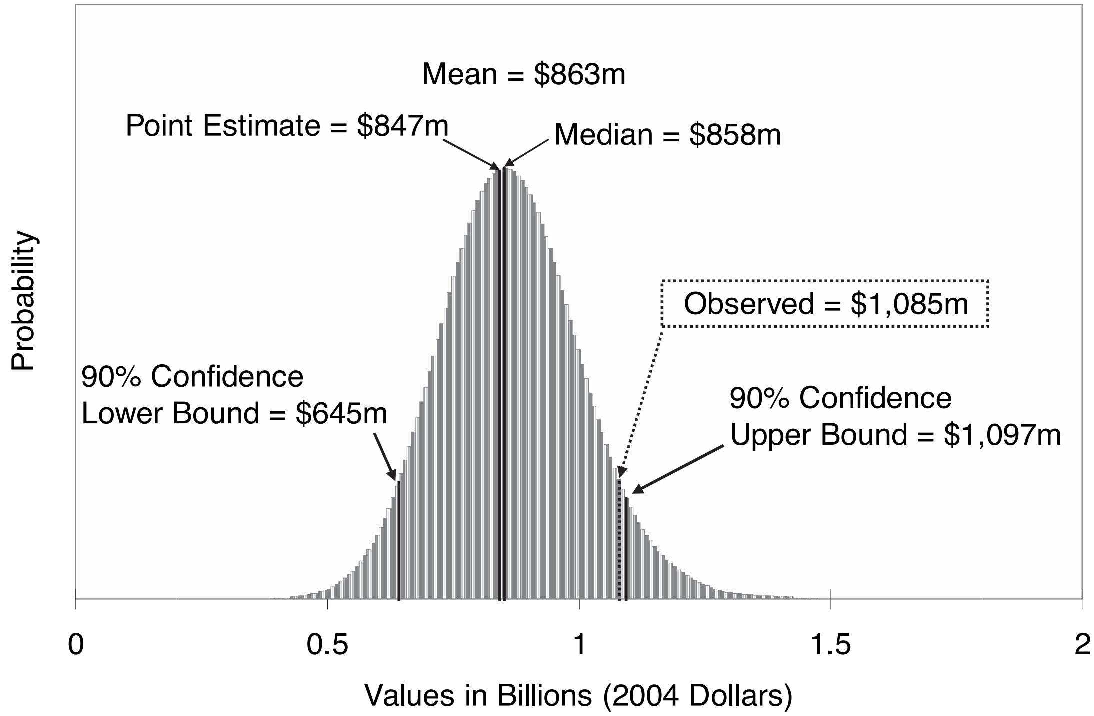

Figure 5. Forecast cost probability mass distribution, fiscal year 2007, made with the fall model, in deflated (fiscal year 2004) dollars.

models also provide evidence that climate-related changes in weather and drought can explain much of the variation in suppression costs over the past three decades. However, there is a systematic trend in overall costs, and this is apparent in all regions except Alaska. Because the components of the trend, including changing fuels, input costs, contracts, and population are highly collinear, we cannot isolate what is responsible for the rising trend. Further modeling, perhaps at smaller spatial scales, could improve our understanding of the individual influences of these factors on the overall positive time trend in costs. Calculations show that the positive secular trends in costs account for a cumulative extra $7.1 billion in suppression costs since 1982 and imply that costs today would be less than half as large if the 1982–2006 secular trends were absent. In practical terms, agency budget officials should take the rising trend into account when making out-year budget forecasts. Additional research is needed that can tease apart the reasons for the rising costs. This could be done through detailed examination of the trends in individual cost components (e.g., as listed in Table 7) across fine spatial scales and over time, by estimating more accurate nonforecasting models (i.e., estimating models using variables corresponding in time with the realized costs), and evaluating how costs may align with factors hypothesized to be linked closely to climate change (e.g., as associated with earlier spring snowmelt and the length of the fire season).

Our forecast models were potentially hampered in their forecast accuracy by cost sharing across regions, which forced inclusion of other regions' drought measures and possibly led to biased and inconsistent parameter estimates for included variables. Despite the fact that we do not know by how much parameter estimates are biased and inconsistent, improved data sets could aid in

Table 7. Percent share of major suppression cost items charged to USFS suppression accounts

	Fiscal year							
Budget category	Average 1993–1994[a]	2000	2001	2002	2003	2004	2005	Average 2000–2005
Salary and benefits	32	29	33	29	32	37	40	33
Supplies	57[b]	7	5	8	5	4	3	59[c]
Contract aircraft		17	18	16	20	21	27	
Emergency equipment rental agreements and other contracts		32	29	36	30	21	14	
Cooperative agreements		4	4	4	8	12	11	
Other	11	12	10	7	5	6	5	8

[a] This is the average of fiscal years 1993 and 1994.
[b] For 1993–1994, only an aggregate of supplies, contract aircraft, emergency equipment rental agreements and other contracts, and cooperative agreements was available
[c] Because of the missing expenditure details for supplies, contract aircraft, and cooperative agreements in 1993 and 1994, only an aggregate annual average for 2000–2005 can be compared with the 1993–1994 aggregate

improving our understanding of costs. One such improvement could occur with the availability of regional time series of for-region expenditures. Although the agency has been tracking these region-sharing expenditures consistently since the late 1990s, a useable time series of own-region only expenditures is still probably a decade off.

Despite these limitations in the data and our models, we have identified cost models that are more precise and accurate than the current model used to forecast USFS suppression costs. Our models reduce RMSEs by 57% for the fall model and 63% for the spring model, compared with the RMSE of the 10-year moving average of costs. Mean absolute percent errors are also smaller using our forecasts, reducing the average percent error by 11 or 12 percentage points, compared with the 10-year moving average. Currently, the 10-year moving average is useful for making budget requests because of its simplicity, limited data needs, and availability further in advance of the target budget year than even our reported fall model. However, our modeling could be extended to produce a forecast with a lead time similar to that provided by the 10-year moving average.

Although these forecast models fit the data well, when forecasted suppression costs are high, as in 2007, the remaining uncertainty in the fall and spring forecasts reduces their potential usefulness. One method that may reduce the uncertainty would combine model forecasts into an ensemble, a common approach in climate and weather forecasting. An ensemble takes advantage of different model structures to reduce uncertainties, allowing for tighter forecast probability distributions. Uncertainties may also be reduced by exploring alternative model functional forms and explanatory variables. In addition, simulation approaches, modeling at alternative spatial and temporal scales, and estimation of models assuming different conditional statistical distributions of suppression costs could yield advances.

Endnotes

[1] This article addresses only the expenditures made by the USFS to suppress wildfires, and the terms "costs" and "expenditures" are used interchangeably.

[2] Testing revealed multicollinearity in the western aggregate equations for fall and spring only. However, in experiments we conducted, dropping any of these variables resulted in a substantial reduction in fit of the estimated models. The available methods are complex and would result in less modeling transparency. Elimination of this multicollinearity is worthy of additional research but is not further pursued in this article. A table of variance inflation factors is available from the authors upon request.

[3] Initially, we estimated individual western region (1–6) cost models separately and then aggregated. The combined models fit worse out-of-sample than in-sample. The by region–for region cost sharing evident in the cost data probably explains this result. We therefore opted to combine them in forecast models.

[4] The fall model equation errors for Regions 8 and 9 did not exhibit significant residual non-normalities.

[5] This form of cross-validation involves iteratively estimating regression models shortened by one observation, which is dropped, and then forecasting the missing observation using the parameter estimates generated from the shortened regression.

[6] Observed emergency suppression costs in fiscal year 2007 ($1,154 million), tallied after this article was drafted, were contained within 90 percent probability bounds of the fall model forecast ($685 million to $1,166 million) and subsequently issued spring model forecasts ($803 million to $1,203 million).

[7] Preliminary tests including the Atlantic Multidecadal Oscillation (NOAA 2007c), motivated by findings by Collins et al. (2006) and Siebold and Veblen (2006), showed that models for Regions 8 and 9 may be improved slightly by including this variable but that models for other regions were not improved. Given limited observations, however, we have limited ability to conduct additional tests.

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Appendix

LCNVC Problems

Two general LCNVC problems can be recognized. One is short-run, small scale, and potentially restricted or constrained, with the minimization defined for a specific fire: minimize the sum of the costs of suppressing that particular fire plus the expected net losses of some specified list of societal concerns (resources, structures, etc.) due to the particular fire. The second problem minimizes a sum across a spatial aggregate, a temporal aggregate, an institutional aggregate, managerial scope, and societal universe of concern. This second problem is the one confronting the USFS.

In the second problem, a spatial aggregate is the summation of all fire-related suppression costs for the spatial unit of inference. The temporal aggregate could be a fire season or multiple fire seasons (say, a planning horizon). The institutional aggregate defines how many organizations are included in the minimization (e.g., in the United States, the USFS, all federal land management agencies, or all land management and fire management organizations).

The managerial scope of this second problem is defined by what specific actions are allowed to vary (i.e., the state variables). These actions can be termed the fire program elements. The scope is defined by the number of elements included in the decision framework. These could include (1) fire prevention, (2) fuels management, (3) presuppression (preseason attack resource placement costs), (4) initial attack or response, (5) (postinitial attack or response) fire suppression, and (6) postfire rehabilitation and recovery. By progressively including elements 1 through 6, the minimization problem becomes progressively less constrained. For example, a minimization that included elements 1 through 6 would choose spending on fire prevention, fuels management, presuppression, initial response, and suppression, given a fixed rate or amount of spending on postfire rehabilitation and recovery such that the sum of the expected net losses from realized fire activity plus those costs included (not postfire rehabilitation and recovery) is at a minimum.

Finally, the societal universe of concern in the second problem refers to how expected net losses related to fires are added up. The expected net losses could be limited to the market value or the net change in economic welfare deriving from damaged resources and structures in the spatial-temporal-institutional unit of inference. The problem could be defined much more broadly, however, including the expected net losses attributable to fire that are experienced in all economic sectors, including nonmarket values. In an economic context, the net losses would be described in welfare terms.

The second problem could also be defined as a multiyear optimization or a long-run optimization, requiring discounting over time. Long run optimization and discounting may be necessary to evaluate the effects of current decisions on future wildfire activity. These include prescribed fire, mechanical fuel treatments, and fuels management activities, which may have effects that last several years. Further, suppressing fires can result in higher rates of future fires or in more intense fires, requiring additional suppression costs (Mercer et al. 2007). A multiyear optimization may be necessary when one is modeling the costs incurred in the suppression activities of individual fire managers, who might not consider long-term impacts of fire suppression actions in active firefighting resource deployments (e.g., Donovan and Brown 2005).

A Theoretical Structure for a Government Agency

We assume that our government agency considers fire management as a LCNVC problem. In addition, we assume that the agency has some indication that historical actions and weather will affect current (or forecast) year spending to suppress wildfires on the lands that it manages. We also assume that the agency's own policy, to prioritize the protection of human lives, public and private property, and natural resources (in that order), affects how much the agency spends on wildfire suppression (US Department of the Interior and Department of Agriculture 1995). Operationally, this last assumption could mean that, as human populations and their structures increase in density in the vicinity of the land that it is charged to protect, spending may rise. However, greater human populations could correspond with greater road density and interruptions in fuel contiguity, which may hinder wildfire spread and enable more efficient suppression resource allocation; the net effect on suppression costs of a human population rise (without controlling for a road density rise) would be unclear.

In the United States, while aggregate spending on fire suppression has increased over time, data are insufficient to demonstrate how various components of costs have changed over time. The largest single component of suppression costs has consistently been salaries and benefits for USFS employees involved in fire suppression (Table 7). When the percentage of expenditures from 1993–1994 are compared with those from with 2000–2005 in three major categories, there is little difference. What this table cannot show, however, is how changes in overhead teams, federal salary increases, and contracting regulations have affected the type of input derived from these expenditures. For example, the "Emergency equipment rental agreements and other contracts" category includes contracts for crews, equipment, food, and showers. For the years for which we have detailed data, some trends can be seen, but the time span is too short to draw conclusions.

Background on Regressor Variables

The Niño3 SSTA

The Niño3 SSTA is used to define the phases of El Niño and La Niña (Trenberth 1997). The models include 1-year lags of the Niño3 SSTA, which is a measure of central Pacific equatorial sea surface temperatures. Niño3 SSTA has been shown to be related to precipitation and temperature in many parts of the United States, where higher positive anomalies ("warm" phase) are correlated with higher precipitation across the southern United States and lower precipitation in the northern tier of states (Swetnam and Betancourt 1990, Brenner 1991, Barnett and Brenner 1992, Prestemon et al. 2002, McKenzie et al. 2004, Mercer and Prestemon 2005, Schoennagel et al. 2005, Kitzberger et al. 2007). Thus, the Niño3 SSTA effects on suppression costs are indeterminate.

SOI

The SOI is a function of the sea level air pressures in Tahiti and Darwin (Australia). The SOI is related to the same central Pacific sea surface (ocean water) temperatures that define El Niño and La Niña. Our hypothesis is that SOI may contain additional information not included in the Niño3 SSTA. Research has linked SOI and wildfire (e.g., Simard et al. 1985; Swetnam and Betancourt 1990, 1998), and SOI has been tied to long-term drought and precipitation variations in the western United States (Cayan et al. 1998). But similar to the above, the effect of SOI on suppression costs could be positive or negative, depending on the strength and duration of the anomaly. Some researchers have used SOI directly in studies of climate and wildfire, but they are using SOI as an indication of ENSO (e.g., Collins et al. 2006).

NAO

The NAO measures the difference between polar low and subtropical high pressure in the northern Atlantic Ocean. Research shows that the NAO is correlated with wintertime precipitation and temperatures in the eastern United States and with other weather anomalies in Alaska. In its positive phase, the eastern United States has milder and wetter winters, whereas in its negative phase, the eastern United States has colder and snowier winters. Again, no previous studies have evaluated NAO and wildfire, although NAO is related to temperature and precipitation patterns in parts of North America (Hurrell et al. 2003), and other correlations have been identified with other Atlantic anomalies (Collins et al. 2006, Kitzberger et al. 2007). We hypothesize that suppression costs for the eastern regions will be positively influenced by NAO.

PDO

The PDO is defined as the first principal component of monthly sea surface variations north of 20° north latitude in the Pacific Ocean. Other research has indicated that the PDO demonstrates patterns similar to the El Niño-Southern Oscillation but that the former exhibits much longer persistence. Several studies have found that the phase of the PDO accentuates the influence of ENSO for wildfire and, thus, we conclude, on costs (McKenzie et al. 2004, Schoennagel et al. 2005, Collins et al. 2006, Kitzberger et al. 2007). It is noteworthy that the PDO has exhibited mainly a positive phase since the 1970s, correlating positively with fire activity in the western United States. But PDO effects on suppression costs are an empirical matter because of its differential expected effects in the northern and southern tiers of states.

AO

The AO measures shifting high- and low-pressure patterns in high northern latitudes of the earth. In its positive phase, it brings drier and warmer than normal weather to the western United States. Previous studies have not attempted to identify the AO as a influence contributing to wildfire. We hypothesize that AO would be related to less moisture in parts of the US west and thus would correlate with suppression costs. The AO has been mainly in its positive phase since the 1970s, perhaps coincidentally corresponding with higher fire activity in the western United States.

PDSI by USFS Region

There are several Palmer indices, corresponding to the average, meteorological, hydrologic, and short-term measures of drought, obtained from the National Oceanic and Atmospheric administration (National Oceanic and Atmospheric Administration (NOAA) 2006c). We tested all of these and used only the western region hydrologic (H) and individual region short-term (Z) measures. A weighted index for each region was developed by weighting the PDSI from each climate reporting district by the USFS acres in that district. PDSI values range from -7 to $+7$, with positive values representing below average drought. We hypothesize a negative relationship between PDSI (both the Z and H measures) and fire activity and thus suppression costs (Westerling 2002, 2003, Crimmins and Comrie 2004, Gedalof et al. 2005, Collins et al. 2006).

Systematic Trends in Costs over Time

Real (dollar-deflated) changes in labor, capital, contracting, and fuel costs have probably influenced spending on fire suppression over the long sweep of time. Further, wildfire fuel buildups related to historical fire suppression and longer term climate changes not captured in other included measures may lead to steady changes in costs over time. In addition, the population in the wildland-urban interface has grown in most parts of the country (e.g., Radeloff et al. 2005). Finally, climate-related changes in length of burn and season lengths (Westerling et al. 2006) could also be systematically evolving over time in a manner that could be captured with a simple trend variable. Because many of these secular changes are highly correlated and those covering the model estimation area sometimes not consistently available, we include region-level time trends to consolidate their joint impacts. It bears mentioning that if all relevant climate-related cost drivers are included in items 1–6, above, then a coefficient on a time trend that is statistically different from zero could capture the aggregate, long-run effect of all other cost drivers, including those associated with an expanded wildland-urban interface, changing private sector aviation and crew contracting costs, and more complicated rule structures faced by wildland firefighters [7].

Error Band Generation

Once point estimates of suppression costs for both forecast lead times are made by applying the estimated suppression cost equations for each of these regions under each forecast lead time, we use a Monte Carlo bootstrapping approach to generate forecast probability distributions for fiscal year 2007. They are made by randomly varying model parameter estimates and randomly adding equation errors to the models before a forecast is made. Following methods described by Krinsky and Robb (1986), these random errors account for cross-equation error and cross-parameter correlations.

Random equation errors are generated by exploiting the estimated correlation matrix of equation errors, $\hat{\Sigma}^{\bullet}$, from the estimates of Equation 5. Let Cov($\mathbf{s}$) be the $N \times N$ symmetric cross-equation regression error covariance matrix, Cholesky[Cov($\mathbf{s}$)] be the $N \times N$ Cholesky decomposition of this covariance matrix, and $\mathbf{Q}_t^N$ be an $N \times 1$ standard normal variate. A random vector of equation errors, $\hat{\mathbf{s}}_t$, which captures the covariances described in Cov($\mathbf{s}$) is therefore $\hat{\mathbf{s}}_t =$

$\mathbf{Q}_t^N \times$ Cholesky[Cov($\mathbf{s}$)]. A matrix of randomly generated parameters that embody the cross-parameter (and cross equation-cross parameter) estimation correlations are similarly generated. Let $\hat{\mathbf{B}}$ be a $1 \times \Sigma_{en} M_n$ stacked vector of the M_n parameter estimates from each of the regions. The $\Sigma_{en} M_n \times \Sigma_{en} M_n$ covariance matrix of these parameter estimates is Cov($\hat{\mathbf{B}}$). Given a $1 \times \Sigma_{en} M_n$ standard normal variate, $\mathbf{Q}^B$, a simulated set of parameter estimates for each iteration of the Monte Carlo is calculated as $\mathbf{B} = \mathbf{Q}^B \times$ Cholesky[Cov($\hat{\mathbf{B}}$)] + $\hat{\mathbf{B}}$, where Cov($\hat{\mathbf{B}}$)] is the Cholesky decomposition of the covariance matrix of parameter estimates. This error perturbed cost forecast process is repeated 50,000 times for all regions simultaneously. Confidence intervals and empirical forecast probability density functions can be described for each region and for an aggregate total (agencywide). To do this, all Monte Carlo-generated forecast values for each region are saved and then ranked from lowest to highest. For example, the 2,250th and 47,750th values in that ranking correspond to the lower and upper bounds, respectively, of a 90% confidence band around the total forecast suppression cost in real dollars for each region and for the agency.