CHAPTER 17

FORECASTING WILDFIRE SUPPRESSION EXPENDITURES FOR THE UNITED STATES FOREST SERVICE

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1. INTRODUCTION

The wildland fire management organization of the United States Forest Service (USFS) operates under policy and budget legacies that began nearly 100 years ago and a forest fuel situation that is all too current. The confluence of these three factors contributes to increased burning and firefighting costs for the agency, and increased concern from both the U.S. Congress and the public. Historically, the 10-year moving average of suppression expenditures has been used in USFS annual budget requests to Congress. But in a time when fire activity and costs are steadily rising, the 10-year moving average budget formula has translated into shortfalls in available suppression funds nearly every year since the mid-1990s. When the budgeted amount is insufficient, the agency continues to suppress fires by reallocating funds from other land management programs and by making subsequent requests to Congress for additional funding. A recent report from the U.S. General Accounting Office (renamed the Government Accountability Office in 2004) recommended a reevaluation of the budgeting system for wildfire suppression expenditures by the federal land management agencies (U.S. GAO, 2004). While many of the issues and critiques made by GAO are beyond the control of the agencies, the USFS has explored alternatives to current practices used in developing out-year budget requests for emergency fire suppression.

We have two primary objectives in this chapter. First, we seek to evaluate candidate forecast models of wildfire suppression expenditures. These time series models are constructed to allow suppression budget forecasts up to 3 years in advance of a coming fire season. These models are evaluated for their suitability for budget documents presented to Congress. The structure of estimated models highlights the importance of accounting for intertemporal dynamics and stochasticity in wildfire suppression expenditures. Second, we demonstrate a method from the forecasting literature that quantifies some of the factors potentially important in choosing among alternative models. The method applies loss functions to errors in forecasts, and our comparisons are between the 10-year moving average and our estimated time series models.

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Budget requests for emergency fire suppression are of particular importance in part because these expenditures are high (they can exceed $1 billion per year) and in part because they are inherently uncertain. Currently, the USFS requests a wildfire suppression budget for a future fiscal year as part of their overall fiscal year budget request for the entire agency, which also includes monies for managing national forests and grasslands, research, and providing assistance to state governments and landowners. If actual wildfire suppression expenditures exceed this budget, the agency is allowed to sequester money from other USFS budgeted programs to continue to suppress wildfires. Congress may, and sometimes does, refund some or all of the sequestered funds, but this leads to uncertainty in the other USFS programs as their funding may be cut partway through the fiscal year. Until recently, Congress made midyear allocations to pay for suppression during high-expenditure years, and the USFS borrowed money from agency controlled trust funds, which are dedicated to activities unrelated to wildfire, to pay for suppression. Over the past few years, however, Congress has made fewer midyear allocations. Additionally, the USFS no longer borrows from the trust funds, such as the Knutsen-Vandenberg Fund, because the agency has not always been able to reimburse these funds immediately due to continued severe fire seasons.

Under the current budget process, the USFS begins to develop a budget request more than two years before the start of the fiscal year in question. Initial budget development uses the best available expenditure data to generate a 10-year moving average for inclusion in the initial budget document. In June 2005, for example, the agency began development of a budget for FY 2007 (October 1, 2006 to September 30, 2007). This budget was based on the ten years of expenditures from FY 1995 to FY 2004 as the FY 2005 fire season had not yet concluded. This is a 3 year out forecast. While the USFS resubmitted a revised budget to USDA in December 2005, the emergency fire suppression budget request was not revised, even though a 2 year out forecast could have been developed as soon as the expenditure accounting for FY 2005 was completed (sometime between October and December of 2005).

Forecasts can lead to costs and benefits for both the agency and the public. Benefits arising from improved accuracy of the forecast may accrue to the public if the total federal budget is assumed to have a maximum—a better forecast will ensure that other USFS programs are completed as originally funded by the U.S. Congress and yet money is not diverted from non-USFS programs to hold for the (poorly forecasted) suppression expenditures. Costs to the USFS could result if the total USFS budget is not allowed to vary with the variation in forecasts for suppression expenditures, in which case a more accurate forecast may mean that funds are diverted from other agency programs to hold for potential wildfire suppression expenditures. These costs and benefits can be represented in loss functions, where values can be assigned to the errors in forecasting. In the final section of this paper, we evaluate the effect of different loss functions on the choice of forecasting models and on the development of the budget request.

2. MODEL OF WILDFIRE SUPPRESSION EXPENDITURES

Wildfire is inherently unknowable in time, place, and extent, but it may be somewhat predictable if fire occurrences are added together up to arbitrary degrees of temporal and spatial aggregation. Uncertainty stems from the randomness of ignitions (whether lightning or human caused), both in terms of frequency and location, as well as from uncertainties associated with fuels and weather. Fuels are, in turn, influenced by longer term trends in both climate and anthropogenic fuel alterations (logging, grazing, prescribed fire, etc.). Historically, overall suppression expenditures have been greater when burned acres are greater, even if economies of scale occur and large fires cost less per acre to suppress than small fires. Figure 17.1 demonstrates the close relationship between acres burned and suppression expenditure for the USFS. However, this relationship is ill-defined, in part because suppression expenditures and burned acres are contemporaneously determined. Nonetheless, this relationship implies that if area burned could be forecast two or three years in advance, then forecasts of expenditures could be developed using area burned forecasts.

The model underlying agency fire management is commonly referred to as the cost plus loss model, or more recently, as the least cost plus net value change model (for example, chapters 13-18 in this book). The agency's objective is to

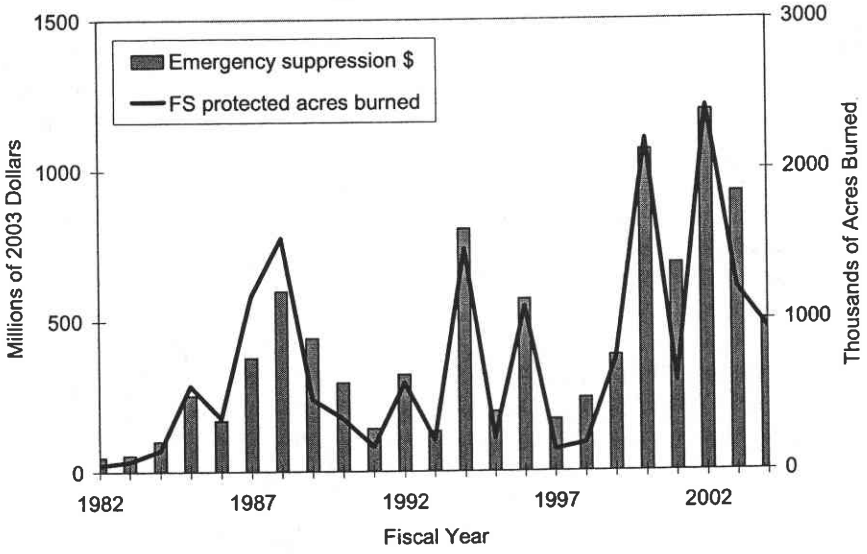

Figure 17.1. Wildfire suppression expenditures by USFS (2003 dollars) and thousands of USFS-protected acres burned, FY 1982 to FY 2004. Data sources: Expenditure data from USFS accounting records managed by the Rocky Mountain Research Station. Fire data are from FS 5100-9 records managed by the National Wildfire Coordinating Group.

minimize the sum of the expenditures associated with fire suppression and the losses associated with fires. Within the overall model, suppression expenditures are minimized along with losses resulting from fires and are subject to ignitions, weather, fuels and human presence, or other factors.

Over time, fuels, ignitions and weather vary as climate and anthropogenic factors change, leading to changes in the forests themselves. To use this type of model for forecasting two and three years out, we would need forecasts of all the included variables, including prices of inputs and values of protected and damaged resources, as well as forecasts of ignitions, fuels, weather and human factors. Even if the model were fully defined and the functional form known or approximated, we do not have the forecasts of independent variables to develop forecasts of costs and losses. Thus, we developed simple time series models with lags of suppression expenditures and a time trend to model suppression expenditures by national forest region.

3. DATA

Suppression expenditure data used in the time series models were based on USFS accounting databases as compiled by the USFS Rocky Mountain Research Station. These data were available beginning in FY 1977 for the nine land management regions, as well as the for the remainder of the Forest Service (RFS), which includes the National Offices, Research Stations, and the National Interagency Fire Center expenditures related to USFS fires.[1] 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. Prior to FY 1994, these data can only be obtained as summaries of expenditures *by* region. After FY 1994, the data can be obtained as summaries of expenditures *for* a region, but this time series was deemed too short as yet to provide reliable statistical results. This issue may be of little importance here as we are using time series models without acres as a covariate (see chapter 15 for more discussion of this issue).

The data series were evaluated and most regional series were log-transformed to approximate a normal distribution. The Southern and Alaska regions and the RFS were estimated untransformed. Note that three of the observations have negative numbers (Pacific Southwest for FY 1998, RFS for FY 1983 and Alaska for FY 1999). These numbers are recorded in the official database as negative because of accounting adjustments that were made after the end of the fiscal year. Unfortunately, we are not able to resolve these negative values, and we must accept them as is. Because the Pacific Southwest data were log-transformed, the FY 1998 value was set to a small positive number and then a dummy variable

[1] Data are available beginning in FY 1971. However, due to the change in FY in 1976 (changed from a July start date to an October start date), only data from FY 1977 on were used in model estimation.

was added for the Pacific Southwest model for FY 1998 to exclude any effects of this variable change on the model and forecasts.

4. TIME SERIES FORECASTING MODELS

We estimated time series models for the nine land management regions and the RFS. The models were estimated and then evaluated at two- and three-year forecast horizons. The three-year forecast horizon may be useful for the initial budget request submitted by the agency, while the two-year horizon could be used to update a budget request several months after the initial request is made. In this analysis, we assume that the budget request can be revised when updated forecasts are available, so that changes in the forecast will affect the budget request and also the budgeted appropriation from the U.S. Congress. Estimated time series models for all regions, summarized in table 17.1, employed various lags of expenditures and a time trend. Where the data had been log-transformed, the forecasts were back-transformed and bias-corrected using a method recommended by Karlberg (2000). In our model selection, we also experimented with unlogged time series models, but out-of-sample performance and non-normality of residuals of these equations in most cases argued for logged versions. The preferred version typically took the natural logarithm of suppression costs for the dependent variable.

For individual models, a model selection procedure which minimizes a model fitting criterion (the Schwarz Information Criterion) was used to identify parsimonious versions of the equations. These models were selected first individually, as least squares regressions of costs as functions of lags of costs (beginning with k=8 lags) and time trends. To account for the unusually low fire expenditures occurring in the Pacific Southwest in FY 1998, where regional costs were reported near zero, a dummy variable was also included.

In most cases, the best-fitting models included one or more lags of costs and a time trend, although selected models for the Rocky Mountain and Alaska regions included just a time trend; for these regions, lagged variables did not significantly explain inter-annual cost variations. Once individual models were determined, the ten regional cost equations were estimated simultaneously, using multiple equation (generalized) least squares, in a Seemingly Unrelated Regression (SUR) (Greene 2003). The SUR method exploits cross-regional correlations in unexplained variation in costs to reduce uncertainties about the values of estimated parameters. The R^2's of individual equations estimated within this system ranged from 0.41 for the Northern Region (Montana and northern Idaho) to 0.92 for the Pacific Southwest Region (California).

Coefficients on many lags of suppression costs included in most of the regional cost equations are estimated to be negative. Negative signs indicate that costly years are followed by cheaper years, and vice versa. This kind of pattern could be capturing cycles in climate, and it may also be demonstrating more

Table 17.1. Model coefficients and fit statistics for the time series forecast model for 10 USFS regions.

	Variables (coefficient; standard error below in parentheses)												
			Year lags										
Region*	Constant	Trend	-1	-2	-3	-4	-5	-6	-7	-8	1998 dummy	R^2	Adjusted R^2
Northern	46.674	**0.177**	**-0.339**	-0.120	-0.087	-0.144	**-0.460**	-0.174	-0.166	-0.492		0.409	-0.075
	(8.346)	**(0.036)**	**(0.137)**	(0.137)	(0.148)	(0.134)	**(0.134)**	(0.153)	(0.152)	(0.152)			
Rocky Mountain	14.235	**0.084**										0.446	0.425
	(0.329)	**(0.016)**											
Southwestern	26.092	**0.138**	0.060	-0.167	**-0.291**	0.031	**-0.332**					0.732	0.637
	(4.788)	**(0.024)**	(0.143)	(0.135)	**(0.126)**	(0.147)	**(0.134)**						
Intermountain	16.937	**0.097**	0.133	-0.038	-0.214							0.552	0.466
	(2.637)	**(0.020)**	(0.112)	(0.114)	(0.117)								
Pacific Southwest	16.996	**0.064**									-9.470	0.917	0.910
	(0.234)	**(0.011)**									(0.392)		
Pacific Northwest	15.310	**0.066**	**0.162**	0.136	**-0.245**							0.528	0.438
	(2.604)	**(0.018)**	**(0.107)**	(0.103)	**(0.107)**								
Southern	41.324	**0.212**	-0.117	**-0.254**	-0.471	0.068	**-0.597**	-0.098	0.036	**-0.368**		0.642	0.349
	(7.342)	**(0.044)**	(0.143)	**(0.137)**	(0.138)	(0.130)	**(0.126)**	(0.127)	(0.124)	**(0.122)**			
Eastern	19.814	**0.089**	-0.004	-0.051	**-0.369**							0.422	0.312
	(3.056)	**(0.024)**	(0.133)	(0.129)	**(0.130)**								
Alaska	-11.198	**0.883**	**-0.425**	**-0.682**	**-0.736**	**-0.606**	**-0.744**	**0.467**				0.697	0.556
	(3.233)	**(0.222)**	**(0.154)**	**(0.161)**	**(0.189)**	**(0.212)**	**(0.204)**	**(0.236)**					
Rest of USFS	-109.748	**11.775**	**-0.455**	-0.170	-0.265	**-0.599**	-0.115	**0.267**	**-0.492**			0.632	0.406
	(36.450)	**(2.815)**	**(0.138)**	(0.150)	(0.155)	**(0.157)**	(0.164)	**(0.163)**	**(0.167)**				

*The costs used in all models besides Southern, Alaska, and Rest of USFS are expressed as natural logarithms. Coefficients significant at 5 percent are bolded.

complicated intertemporal budget reallocations. Additional research into the underlying climate factors driving fire activity and the economic factors driving costs could improve our understanding of these results. It is notable that the trend is positive and statistically significant (at 5 percent) for all models. This finding documents the universally positive trend in real suppression costs for the USFS over the estimation period.

4.1 Forecast Confidence Intervals

The estimated models can be used to develop not only a point forecast, but can be used to develop a distribution that will provide an estimate of the confidence intervals for the forecasts. To develop the distributions, we employed techniques described by Krinsky and Robb (1987). These distributions account for the uncertainties in the equations estimated and reported in table 17.1. Uncertainties include those associated with parameter estimates and equation residuals. The Krinsky and Robb (1987) approach accommodates, as well, correlations across estimated parameters and equation residuals. In the discussion below, the forecasts are in both constant (2003) dollars and inflated (current 2007 or 2008) dollars for the year being forecasted.

Table 17.2 shows the FY 2007 forecast, using the time series models and data available in early October, 2005. The median forecast of FY 2007 USFS suppression expenditures, implying a 50 percent chance that expenditures will exceed the value, is $1,096 million (in projected 2007 dollars), with the 95 percent confidence interval ranging from $436 million to $2,904 million. The probability-weighted (expected or mean) forecast expenditure is $1,242 million, while the most likely single value (point forecast) is $1,015 million. The distribution of the forecast for FY 2007 (in constant 2003 dollars only) is shown in figure 17.2.

Table 17.3 and figure 17.3 show the FY 2008 forecast using the time series model and data through early October, 2005, as the input data set, creating the 3 year out forecast. The median forecast of FY 2008 suppression expenditures

Table 17.2. Confidence interval table for forecast of total USFS wildfire suppression expenditures for FY 2007.

	FY 2007 forecast millions of 2003 dollars	FY 2007 forecast millions of 2007 dollars
Point forecast	907	1,015
Mean	1,111	1,242
Median	980	1,096
95% confidence interval lower bound	389	436
95% confidence interval upper bound	2,596	2,904
90% confidence interval lower bound	453	507
90% confidence interval upper bound	2,208	2,469

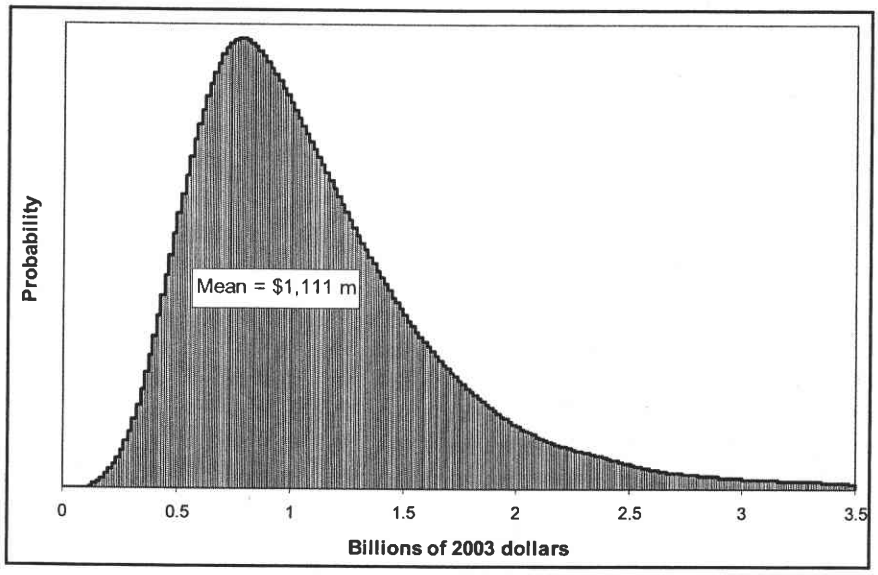

Figure 17.2. Empirical probability density of the forecast of total USFS wildfire suppression expenditures for FY 2007, in constant (2003) dollars.

Table 17.3. Confidence interval table for forecast of total USFS wildfire suppression expenditures for FY 2008.

	FY 2008 forecast millions of 2003 dollars	FY 2008 forecast millions of 2008 dollars
Point forecast	1,039	1,197
Mean	1,230	1,417
Median	1,096	1,262
95% confidence interval lower bound	493	567
95% confidence interval upper bound	2,760	3,179
90% confidence interval lower bound	556	641
90% confidence interval upper bound	2,345	2,701

is $1,262 million with the 95 percent confidence interval ranging from $567 to $3,179 million. The mean forecast is $1,417 million, while the most likely single value is $1,197 million.

4.2 Forecasts and Model Comparisons

To evaluate the time-series models in conditions approximating real-world budget forecasting, we developed out-of sample, cross-validated forecasts of agency-wide (total) suppression expenditures. Agency-wide totals of suppression are simply

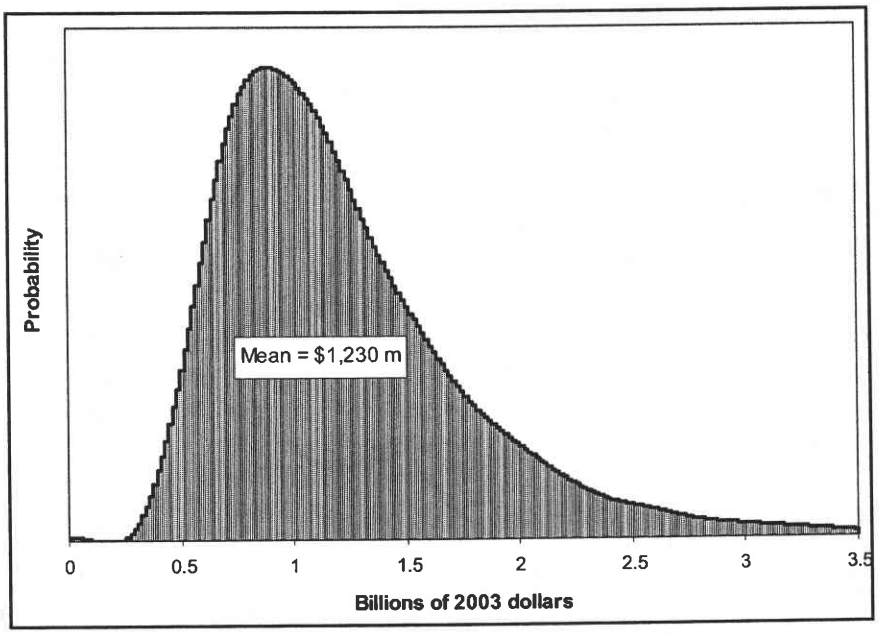

Figure 17.3. Empirical probability density of the forecast total USFS wildfire suppression expenditures for FY 2008, in constant (2003) dollars.

the sums of the forecasted expenditures for each region in each year forecasted. The cross-validation is achieved by leaving out the forecast year observation, estimating the model, and then forecasting the left-out observation, for all years. This cross-validation is done region by region, and the cross-validated forecast values are then summed across all ten regions. These forecasts and actual expenditures are displayed in figure 17.4 and used in the model evaluations presented in tables 17.4 and 17.5.

We find that the agency-wide actual expenditures are more volatile than the forecasts, regardless of the model used (fig. 17.4). This implies that there is important information not captured in the time trends or lags of costs. Figure 17.4 shows the total USFS expenditures and the total USFS forecasts using the 10-year moving average and the 2 year out and 3 year out time series models. Also included is the time series of actual expenditures . The 10-year moving average is calculated and shown for both two- and three-year horizons, which allows for a more direct comparison between the time series and 10-year moving average models. In other words, the 2 year out time series model should be compared with the 2 year out moving average model, and the 3 year out time series model should be compared with the 3 year out moving average model.

Fitness statistics document the performance of the alternative forecast models (table 17.4) as quantified by the root mean squared error (RMSE) and the R^2 of

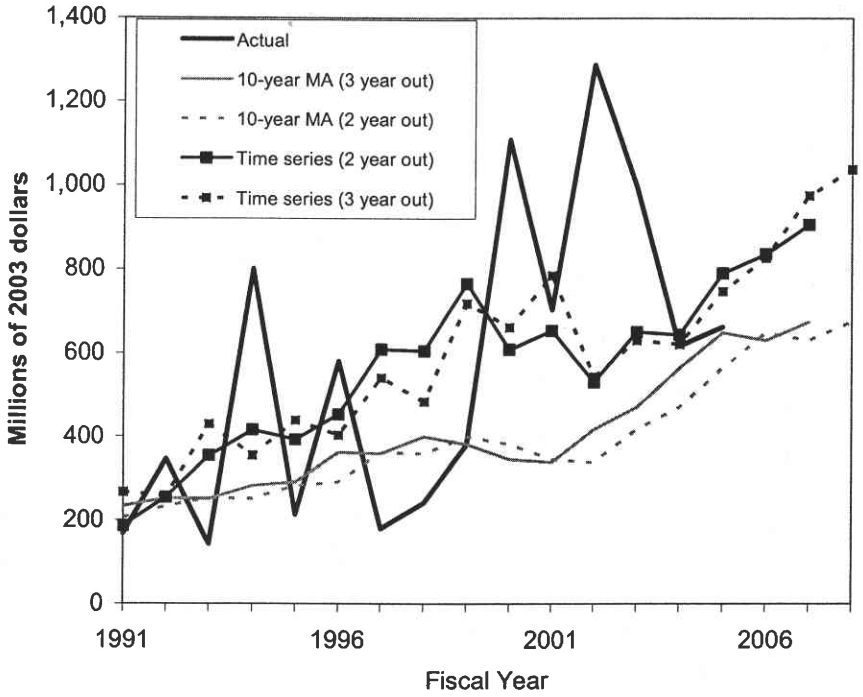

Figure 17.4. Actual total USFS wildfire suppression expenditures compared to forecast total USFS expenditures for the 10-year moving average (MA) and time series forecast models for 2 and 3 years out.

Table 17.4. Root mean squared error (in millions of dollars squared) and cross-validated (jackknife) R^2 for suppression forecasting models for 15 years (FY 1991-FY 2005) and 5 years (FY 2001-FY 2005).

	FY 1991-FY 2005 RMSE	FY 2001-FY 2005 RMSE	FY 1991-FY 2005 R^2	FY 2001-FY 2005 R^2
Time series—2 year out	346	486	0.73	0.80
Time series—3 year out	337	419	0.76	0.82
10 year moving average—2 year out	376	619	0.69	0.67
10 year moving average—3 year out	413	591	0.64	0.65

Table 17.5. Significance tests (F) for RMSE between 2 and 3 year out models and between time series and moving average models for 15 years (FY 1991-FY 2005) and 5 years (FY 2001-FY 2005).

	FY 1991-FY 2005	FY 2001-FY 2005
Critical F Statistic	2.48	6.39
Degrees of freedom	14	4
Time series (2 year out vs. 3 year out)	1.05	0.61
10 year moving average (2 year out vs. 3 year out)	1.09	1.75
2 year out (time series vs. 10 year moving average)	1.07	1.31
3 year out (time series vs. 10 year moving average)	0.93	1.23

cross-validated forecasts. These statistics are calculated for the longest common comparison set of years and more recent years, the latter set containing higher average levels of observed suppression expenditures (fig. 17.4) and providing some evidence of model performance in the most recent years of forecasting. Over both sets of years, the 3 year out time series model has the lowest error (RMSE of 346 million) and highest jackknife R^2 (0.76) of all the models, followed by the 2 year out time series model (RMSE of 346 million, jackknife R^2 of 0.73) over FY 1991-FY 2005. Ten year moving average forecasts have RMSE's that are higher by at least 30 million over the comparison set of years. All four models demonstrate a poorer fit in more recent years, when costs have been generally higher. That, however, would be expected, even if the percentage errors were to remain the same. Indeed, the jackknife R^2's for all models are higher over the FY 2001-FY 2005 period.

Unfortunately, we have a short time series of forecasts with which to compare our forecasts with observed costs, and this shortness makes it difficult to discern whether any model is superior to the other in terms of these two measures of fitness. F-tests can be used to compare the RMSE's (table 17.5). This simple ratio of variances test, distributed as $F_{n-1,n-1}$ where n is the number of observations used to calculate the mean squared errors (assuming normality), produces test statistics for the comparisons between 2 and 3 years ahead for both model types, and for the comparisons between the time series and 10-year moving average at both 2 and 3 years ahead. We find that none of the models is statistically significantly superior to any other model at the 5 percent significance level.

Comparisons such as those shown in tables 17.4 and 17.5 are meaningful for policy makers seeking to select among competing models when the policy maker places value only on forecast accuracy and when errors in forecasts generate losses to the agency that are linear in these errors. In contrast, if a decision maker cares about the direction (positive, negative) of these errors, then the RMSE is not informative. Likewise, if the decision maker cares relatively more about large errors than small errors (per dollar of error, say), then the

RMSE is not informative, and neither is the jackknife R^2. More specifically, these error comparisons based on the RMSE assume that (1) the losses associated with suppression expenditure forecasting are symmetric and linear, (2) the only losses are those associated with error, and (3) the point value of the forecast was used for budget allocations. These assumptions and the effects of altering these assumptions (shape of loss functions, multiple loss functions, and choice of forecast level for budgeting) are discussed further in the following section.

5. LOSSES ASSOCIATED WITH FORECASTS

As Lawrence and O'Connor (2005) summarize well, the primary objective in most economic forecasting is accuracy—minimizing forecasting error. But, they state, for some organizations, the economic or non-economic costs (or losses) associated with forecasting errors can differ according to highly nonlinear valuation criteria. Sometimes, the error associated with forecasting too high may have different implications than the same size error associated with forecasting too low. Some organizations may identify an error band within which forecasting errors have lower losses associated with them compared to errors that surpass the band. Alternatively, the losses associated with forecasting errors may steadily increase, or may increase in a nonlinear fashion per unit of forecasting error as the absolute size of the error goes up.

Losses associated with forecasting errors may arise from a variety of mechanisms. They may arise out of investment errors caused by a forecasting error—over- or under-investing in anticipation that the state of the world will be at a certain level in the future. They can also arise from the opportunity costs associated with diverting scarce administrative resources to making accounting adjustments across budget categories of an organization's overall budget. A challenge for an organization seeking to improve forecasting is to quantify how forecasting errors translate into losses for the organization.

The losses associated with these kinds of errors have been identified as significant in the case of budget under-predicting (budgeted less than actual) for wildfire suppression expenditures (U.S. General Accounting Office 2004). Losses associated with under-predicting occur when either (1) the agency must reallocate internal funds to pay for higher than forecast suppression expenditures, or (2) insufficient crews (contract or agency) are available to suppress fires at the start of the season leading to increased contracting or hiring costs during the season (Donovan 2005). A second type of loss results from over-predicting (budgeted more than actual), where budgets for other programs and activities are reduced in order to maintain sufficient funds for potential suppression expenditures when those expenditures are less than predicted.

Thus, although there are potential costs associated with inaccurate budgeting for fire suppression, what constitutes an improved forecast will depend on how the losses and budget request decisions are defined. The suppression expenditure

forecast models presented above were developed using classical statistical criteria of minimizing the sum of squared errors and minimizing bias (the tendency to over- or under-predict). However, optimal budget allocation models do not need to be so narrowly (or perhaps naïvely) focused, and sometimes other measures of forecast fitness (e.g., mean absolute percent error of forecast) may be more important indicators of a model's usefulness.

To reiterate an earlier point, forecasts above assumed that (1) the point forecast value is used to make a budget request and the budget request is met at that same point forecast value, (2) perceived losses associated with budgeting errors are symmetric (e.g., a budget created by the forecast that exceeds the observed amount by $100 million creates the same loss for the agency as a budget that is $100 million less than the observed amount), (3) perceived losses are linear (a $100 million error is twice as bad as a $50 million error), and hence that (4) error minimization is the only forecasting objective. Nonetheless, Lawrence and O'Connor (2005), Granger and Pesaran (2000), and evidence described above about the agency decision on suppression fund allocations imply that decision makers may have loss functions that depart from purely statistical criteria. Below, we discuss the shape and multiplicity of loss functions. We follow that with a discussion of how these losses can be used to develop a tool for choosing an optimal forecast value to use for budget requests. The forecast models used in the following discussion include the 2 year out models for both the time series and the 10 year moving average.

5.1 Shape of Loss Functions—Symmetry and Linearity

Sometimes the consequences of over-predicting versus under-predicting are the same (symmetric loss), while other times it is more problematic to over-predict than to under-predict, or the opposite (asymmetric loss). From the USFS perspective, it may be worse to under-predict as this leaves the agency without sufficient funds for suppression (and they violate anti-deficiency regulations) unless funds are borrowed from other USFS programs. However, in some cases, the agency may determine that it is worse to over-predict because it leads to sequestering of funds in advance of the fire season that could be utilized elsewhere.

A second factor affecting the calculation of losses from forecasting is the presence of thresholds—levels above or below which losses per unit of error change. Some forecasts may be associated with no losses for small errors, or may have distinct losses associated with specific ranges of errors. For example, a forecast that is off by $10 million may cause few or no problems, but as the error increases above that level, problems increase. There are infinitely many forms that these loss functions could take and values that could be attributed to the various losses.

5.2 Multiple Loss Functions

Baumgarten and James (1993) suggest that federal budgets are adjusted only incrementally for most years, until some external change occurs that leads to

jumps in particular budgets, leading to a new epoch of cost levels. The USFS budget also demonstrates this incremental-epochal characteristic, where most years have budget changes of less than 6 percent, net of inflation dollar terms. The three years following the 2000 fire season and the implementation of the National Fire Plan can be characterized as epochal, where the total USFS budget increased by more than 40 percent. The trend seems to have reverted to incremental for 2003-2005, with annual changes of less than 5 percent for the last two years, but costs in 2006 were again among the highest ever observed for the agency.

These trends could be important for emergency fire suppression forecasting because a forecast made using the time series model is usually more variable than a forecast made using the 10 year moving average. If the entire USFS budget (for emergency fire suppression and all other activities) is limited in incremental years to increases of no more than 6 percent, say, then forecasted suppression budgets that exceed this rate of increase will have to be accommodated internally by reducing budgets for other agency programs. Thus, one possible objective of a preferred budget allocation model could be to maintain stability in the suppression budget requests made by the USFS to Congress. While stability would seem to imply that agency spending would occasionally need to be reallocated late in a budget year, some of the losses associated with late budget year reallocations can be avoided through special supplemental budget requests by the agency to Congress. The 10 year moving average model dampens budget request volatility and hence could continue to be used to achieve this stability.

Alternatively, another objective for agency planners could be to improve the accuracy of budget requests using a statistical budget forecasting tool. This would require the agency to submit more volatile annual budget requests (in total, suppression plus other agency spending). It is unclear how the oversight agencies and Congress would respond to this type of budget request volatility. Depending on the shape of the loss function, and the values associated with the losses, either model (time series or moving average) could be preferred if losses are lower with one than the other.

5.3 Designing an Improved Budget Request Tool

A budget request tool should include the values of the losses, for both over- and under-predicting (symmetry), stability, accuracy, and threshold values (linearity). If values were known for these losses (e.g., one unit of loss of accuracy could cost $1) an optimal choice, or even combination, of forecast models could be used to develop a forecast value. Alternatively, the probability that the budget is sufficient to cover expenditures could be varied, allowing a value to be chosen that would reflect an optimal budget request amount given the losses. The RMSE and R^2 model evaluations are based on an assumption that the point forecast is used for budget requests and appropriation. For the evaluations of shape and objectives, we used the median forecast, which implies that there is a 50 percent chance that the budget request will be exceeded by actual costs.

Table 17.6 reports the results of a series of simulations where loss values, functions and objectives were varied. The simulations were conducted for both the time series and the 10 year moving average forecast models. We assumed in our simulations that (1) stability and accuracy were the two objectives jointly sought by the agency; (2) stability was defined as variation between the budgeted amount in year t and year t-1; (3) accuracy was defined as variation between budgeted and actual amounts in year t; (4) stability was given a symmetric loss (i.e., the absolute value of an under-prediction generated the same loss as an equivalent absolute value of over-prediction), but was evaluated with both (i) constant loss values and (ii) a threshold absolute value, $100 million, below which errors had a loss of zero, (5) accuracy was valued both symmetrically and asymmetrically, and for both linear losses (constant loss per dollar of under-or over-prediction) and nonlinear losses (threshold=$100 million, below which loss=0).

The first salient result of our simulations, shown in table 17.6, is that when over-budgeting (actual < budgeted) for the fire season is more costly than under-budgeting (actual > budgeted), then the 10-year moving average model would be preferred. Similarly, if instability in budgets is more costly, then the 10-year moving average model outperforms the time series model. However, when under-budgeting is more costly (actual > budgeted), the time series models are preferred. There are, however, many alternative objectives, shapes and loss values that do not result in a clear preference for one model over the other. Estimating or collecting loss values, objectives and shapes of functions could be used to develop a budgeting tool, either by choosing the best performing model, or possibly by developing a combination (or ensemble) forecast from the two models that would outperform either model independently.

A second method of developing a budget request tool could utilize the forecast distribution for a particular fire season's expenditures (e.g., figs. 17.2 and 17.3 above) that can be developed for both forecast models. Using this distribution for the time series models and the loss values for accuracy, the optimal budget request may be a figure different from either the point, mean or median forecast from the model. Table 17.7 shows the budget request that minimizes the losses (FY 1991 to FY 2005) from over- and under-budgeting. The first simulation assumes that each dollar of loss has a value of $1 to the agency. With a 50 percent (median) budget request, the losses (the same as in table 17.6) are $4,424 million. By making a budget request that would provide a lower probability (44.3 percent) of being exceeded (i.e., a lower "probability of ruin"), this value could be reduced to $4,375 million. Similarly, total losses resulting from other assumed loss values and shapes can be reduced by either increasing or decreasing the probability of ruin.

6. CONCLUSIONS

The current forecast model used for out-year budgeting for the USFS is the 10-year moving average. Development of more sophisticated time series models,

Table 17.6. Simulations of losses from variations in loss functions resulting from forecasting suppression expenditures using the 10 year moving average and time series models.

Definition of alternative		Total Losses from Forecasting (mm$), 1991-2005		Values of losses ($/unit)					
				Accuracy				Stability	
				Asymmetric Actual>predicted		Asymmetric Actual<predicted		(always symmetric)	
				Above or below threshold (linearity)					
Shape of loss function	Objective	If 2 year out time series model used for budgeting	If 2 year out 10 year moving average model used for budgeting	Below	Above	Below	Above	Below	Above
Symmetric and linear	Accuracy only	4,424	4,433	1	1	1	1	0	0
Symmetric and linear	Stability only	1,320	629	0	0	0	0	1	1
Symmetric and linear	Accuracy & Stability	5,744	5,062	1	1	1	1	1	1
Asymmetric (accuracy) and linear	Accuracy only	7,104	8,274	2	2	1	1	0	0
Asymmetric (accuracy) and linear	Accuracy only	6,128	5,024	1	1	2	2	0	0
Asymmetric (accuracy) and linear	Accuracy & Stability	8,424	8,903	2	2	1	1	1	1
Asymmetric (accuracy) and linear	Accuracy & Stability	7,488	5,653	1	1	2	2	1	1
Symmetric and nonlinear	Stability only	2,490	1,118	0	0	0	0	1	2
Symmetric and nonlinear	Accuracy & Stability	9,852	8,577	1	2	1	2	1	2
Symmetric and nonlinear	Accuracy & Stability	8,682	8,089	1	2	1	2	1	1
Asymmetric (accuracy) and linear	Accuracy & Stability	9,744	9,532	2	2	1	1	2	2
Asymmetric (accuracy) and nonlinear	Accuracy & Stability	8.808	6,282	1	1	2	2	2	2

(continued)

Table 17.6. Simulations of losses from variations in loss functions resulting from forecasting suppression expenditures using the 10 year moving average and time series models. ***(continued)***

Definition of alternative		Total Losses from Forecasting (mm$), 1991-2005		Values of losses ($/unit)					
				Accuracy				Stability	
				Asymmetric Actual>predicted		Asymmetric Actual<predicted		(always symmetric)	
				Above or below threshold (linearity)					
Shape of loss function	Objective	If 2 year out time series model used for budgeting	If 2 year out 10 year moving average model used for budgeting	Below	Above	Below	Above	Below	Above
Asymmetric (accuracy) and nonlinear	Accuracy & Stability	10,002	8,718	1	2	1	2	2	2
Asymmetric (accuracy) and nonlinear	Accuracy & Stability	9.504	9,392	2	2	1	1	1	2
Asymmetric (accuracy) and nonlinear	Accuracy & Stability	8,658	6,152	1	1	2	2	1	2
Asymmetric (accuracy) and nonlinear	Accuracy only	7,362	7,459	1	2	1	2	0	0
Asymmetric (accuracy) and nonlinear	Accuracy only	5,910	5,838	2	1	2	1	0	0

Table 17.7. Simulations of losses from variations in budget request percentage (probability of ruin) resulting from forecasting suppression expenditures using the 10 year moving average and time series models.

Shape of loss function	Total loss (mm$)	Asymmetric Actual>predicted		Asymmetric Actual<predicted		Budget request percentage (probability of ruin)
		Below	Above	Below	Above	
Symmetric and linear	4,375	1	1	1	1	44.3
Asymmetric (accuracy) and linear	6,199	2	2	1	1	35.6
Asymmetric (accuracy) and linear	5,906	1	1	2	2	64.5
Asymmetric (accuracy) and nonlinear	7,317	1	2	1	2	45.4
Asymmetric (accuracy) and nonlinear	5,807	2	1	2	1	44.3

and particularly time series with covariates that can explain variations in fire activity and costs beyond variation explained by lags of costs and time trends, may improve the accuracy of expenditure forecasts. These models could be informed by research reported by Swetnam and Betancourt (1990), Westerling et al. (2002, 2003) and Collins et al. (2006). Our modeling faced severe data constraints when seeking to understand the time series nature of wildfire suppression costs. We have short time series, which limited our inferential and model selecting abilities. Symptomatic of the data constraints was the fact that neither of the proposed time series out-year models provided forecasts that were statistically significantly better (using variance ratio tests) than the current agency approach to budgeting. However, there are likely to be other factors that will, and should, influence the choice of optimal forecasts, such as the costs to the agency, the public and the oversight agencies resulting from the always imperfect forecasts. We have described a set of procedures, involving loss functions, that could help agency decision makers to design a budget request tool that balances desires for both accuracy and stability or that minimizes the costs associated with over- or under-budgeting. For example, if the cost of having a budget that is insufficient to cover costs is very high, then the time series models may be preferred. Alternatively, if the cost of having too high a budget is very high or if the cost of a variable budget is very high, then the 10 year moving average is preferred. Because the 10 year moving average is the currently selected budget tool, this may reflect the possibility that the agency or U.S. Congress loss function has high costs of over-budgeting or variability.

Ultimately, advances in our understanding of how to forecast wildfire activity at multiple spatial and temporal scales can be achieved only through additional

research and observations. Each new season of wildfire and suppression generates new information that can be used to identify better performing models. Research has shown that fire activity is closely related to droughts, precipitation levels, temperatures, and length of seasons (Schoennagel et al. 2003, Schoenberg et al. 2003, Westerling 2006, Kitzberger et al. 2007), many of which are forecastable using ocean temperatures, sea level pressures, and other ecological indicators. As climate science advances, longer-term climate forecasts may become available and be potentially useful for forecasting fire season activity and expected costs with greater accuracy.

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