Forecasting Resource-Allocation Decisions Under Climate Uncertainty: Fire Suppression with Assessment of Net Benefits of Research

Jeffrey P. Prestemon and Geoffrey H. Donovan

Making input decisions under climate uncertainty often involves two-stage methods that use expensive and opaque transfer functions. This article describes an alternative, single-stage approach to such decisions using forecasting methods. The example shown is for preseason fire suppression resource contracting decisions faced by the United States Forest Service. Two-stage decision tools have been developed for these decisions, and we compare the expected gains to the agency, in terms of reduced personnel costs, of the single-stage model over the two-stage model, existing hiring decisions, and decisions that would have been made given perfect foresight about wildfire activity. Our analysis demonstrates the potential gains to versions of our single-stage model over existing hiring decisions, equivalent to a benefit-cost ratio of 22. The research also identified additional gains accruing from imposing biases on the single-stage model, associated with asymmetric penalties from contracting decisions.

Key words: climate, forecast, forest service, Poisson, returns to research, wildfire suppression.

Public and private sector managers must regularly make input-allocation decisions with consequences that depend on future states of nature. Because these states of nature are not known with certainty, the decisions, when evaluated *ex post*, are often suboptimal. For example, at the beginning of a growing season, a farmer must decide what crops to plant, but the consequence of this decision depend on future weather and market conditions. Given better information about future states of nature—amount of rainfall, for example—the farmer would probably make more profitable input allocations.

The value of information about future climate conditions, and its potential to improve production decisions, has received particular attention in the literature. Studies of this type have typically taken a two-stage approach to decision making. First, they obtain conditional forecasts of one or more climate variables. Second, they process the forecast data using a transfer function (Johnson and Holt 1997) that uses the forecast variables to identify the best input-allocation decision. To estimate the value of the forecasts, they compare decisions made with and without the forecast information. Examples of this approach include Costello, Adams, and Polasky (1998) and Chen, McCarl, and Hill (2002), who use forecasts of the El Niño-Southern Oscillation (ENSO) to make decisions on fish harvest levels and crop mixes, respectively.

There are a number of difficulties with such a two-stage approach. First, transfer functions are often complex and have the potential to become a black box, obscuring the value of the information contained in the climate forecasts (Johnson and Holt 1997). Second, a two-stage analysis may obscure the multiple sources of uncertainty inherent in complex natural systems. Often, the forecast variables contain their own uncertainties, having been obtained from secondary sources, and the use of just forecast variables potentially limits consideration of other predictive factors. Finally, the information requirements and costs of such an approach may be high.

We suggest a simpler and potentially more accurate single-stage approach to improving input allocations given uncertainty. This

Jeffrey P. Prestemon is research forester, Forestry Sciences Laboratory, Southern Research Station, USDA Forest Service and Geoffrey H. Donovan is research forester, Forestry Sciences Laboratory, Pacific Northwest Research Station.

The authors thank Stephanie Snyder and Brandon Collins for their reviews of an earlier draft of this article. They also thank *AJAE* Editor Stephen K. Swallow for his helpful comments in various stages of manuscript development while in review at *AJAE*. Funding for this study was partially provided by the USDA Forest Service's National Fire Plan.

Amer. J. Agr. Econ. 90(4) (November 2008): 1118–1129
Copyright 2008 Agricultural and Applied Economics Association
DOI: 10.1111/j.1467-8276.2008.01152.x

approach requires development of a statistical model. The dependent variable in this model is a time series of cost-minimizing *ex ante* decisions, given *ex post* information about the future state (i.e., decisions made with perfect foresight). In the example that we describe in this article, the regressors available *ex ante* are lagged climate variables rather than forecasts of future climatic conditions. In our empirical example, we quantify the expected net gains of the single-stage model over other approaches, including a two-stage approach. The single-stage approach has several advantages over a two-stage approach. First, there is no need to construct a transfer function. Second, a single-stage model, which directly predicts the cost-minimizing decision, more transparently deals with uncertainty. Third, the approach has modest data requirements.

To demonstrate the application of our proposed approach, we use an example from wildfire management—a topic of interest to researchers, policy makers, and the general public. Prior to the start of a wildfire season, public land managers must make a number of input-allocation decisions including how many fire crews to hire. The crew-hiring decision has been the subject of previous research (Donovan 2006). The choice of how many fire crews to hire is just one decision of several (including spending on fuel-reduction treatments, aviation contracting, new equipment purchases, etc.) that the U.S. Department of Agriculture (USDA) Forest Service (hereafter, "USFS") and other land management agencies must make under uncertainty each fire season. The consequences of these decisions are not trivial, as, since 2000, federal agencies have spent an average of nearly one billion dollars annually putting out wildfires (National Interagency Fire Center 2007). A number of factors have contributed to these record-high costs including development patterns and climate change (McKenzie et al. 2004; Westerling et al. 2006). A decision model that is able to improve the efficiency of input allocations could generate significant cost savings. Potential applications of our proposed approach are not limited to wildfire management, however. Our parsimonious approach to decision making under uncertainty could be readily applied to other sectors such as agriculture, transportation, or fisheries.

The remainder of this article is organized as follows. We begin by describing the USFS crew-hiring decision. Next, we outline a theoretical structure for evaluating how improved information can result in net economic gains. Following this, we detail how data sets needed for the single-stage model are generated. The results section compares the performance of the single-stage approach to alternative decision frameworks. We conclude by describing how climate change could affect the performance of the single-stage approach.

Methods

Interest in quantifying the benefit of forecasts may predate the available scientific literature, but recent published studies can provide perspective about how the present study is unique. Much research has focused on the value of forecasts of future ENSO conditions, as determined by a transfer function. For example, Costello, Adams, and Polasky (1998) provide an example of the benefits of ENSO forecasts for the salmon fishing industry of the United States. The authors input forecasts of future ENSO conditions into a transfer function consisting of a dynamic programming model of fishing industry production. Chen, McCarl, and Hill (2002) evaluate how improved ENSO forecasts lead to welfare benefits in the agricultural sector by inputting the forecast into a transfer function specified as a multiproduct spatial equilibrium model of world agricultural markets. Considine et al. (2004) quantify the value, in terms of expected damages to the oil and gas industry, of improved accuracy of forty-eight-hour hurricane tracks in the Gulf of Mexico. The transfer function is a decision model for oil and gas rig storm preparation and evacuation. Brown and Murphy (1988) quantify the value of daily fire-weather forecasts at reducing the total costs and losses from wildfire. Their transfer function is a decision model to allocate fire suppression resources across multiple wildfires, and the fire-weather forecasts serve to reduce, compared to average expected weather, the sum of the expected suppression costs and wildfire damages.

The Agency Choice

Before the start of a fire season, USFS managers must decide how many agency fire crews to hire. Because agency crews are hired for an entire season, some crews may be idle during periods of low demand. During periods of high demand, managers must supplement agency crews with more expensive contract crews (figure 1). Although contract crews are more expensive, they are also more flexible

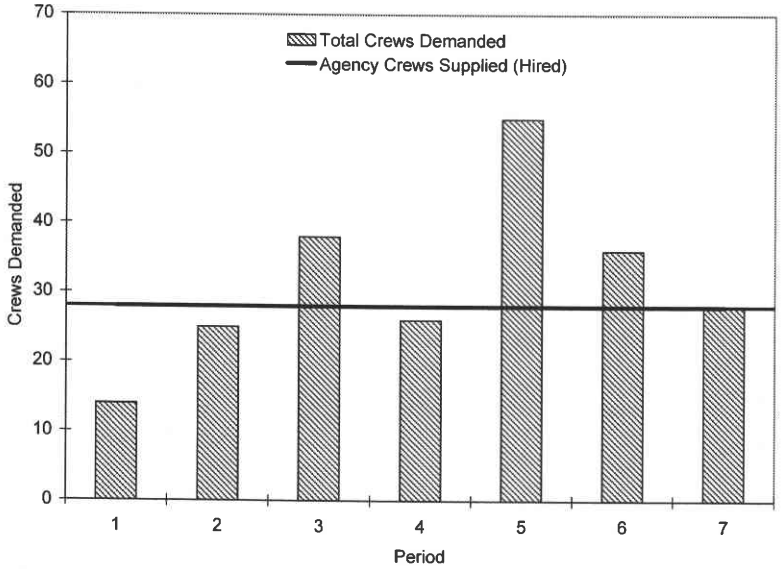

Figure 1. An example of crew demand and number of agency crews hired during a seven-period fire season, demonstrating the mismatch between number of crews hired in advance of the season and the observed demands for crews during the season

and can be laid off when not needed. However, the cost advantage that agency crews have over contract crews depends on the availability of work: if agency crews stand idle for too long, then they lose this cost advantage (Donovan 2005).[1]

The problem facing managers is to hire the cost-minimizing number of agency crews, given uncertainty about fire activity in an upcoming season. Donovan (2006) presents a mixed integer program that uses historical fire occurrence data to make a crew-hiring recommendation. We make use of this previous work in three ways. First, we use the model to generate a time series of perfect-foresight hiring decisions. For a particular season, the perfect-foresight decision produces the absolute minimum cost the agency could incur if it knew in advance precisely what the coming fire season's crew demands were going to be. Imperfect knowledge about the future makes the perfect-foresight decision the benchmark against which to compare alternative hiring-decision strategies. Second, we compare the hiring recommendations of this model to our new single-stage statistical model. Third, we use the model as an accounting tool to calculate the cost of crew-hiring recommendations.

Theoretical Development

Johnson and Holt (1997) describe how information about the likelihoods of future states can lead to enhanced expected utility of an economic agent making decisions affected by the future states. The description begins by defining a set of actions, $a = 1, \ldots, N$, that the economic agent can take, and a set of future states, $s = 1, \ldots, M$, over which the agent has no direct control but whose probabilities of occurrence influence the expected utility-maximizing choice of a. Furthermore, they define the consequences of the choice a when state s occurs as $c(a, s)$. The consequence could be a level of profit or cost, or it could be a multidimensional set of outcomes. Each $c(a, s)$ has a level of utility associated with it, $u[c(a, s)]$, for all possible combinations of actions and states. The agent's objective, under risk-neutrality, is to maximize expected utility by selecting an action a_0 (Johnson and Holt 1997, p. 79):

$$(1) \qquad E\{u[c(a_0, \cdot)]\} = \max_a E\{u[c(a, \cdot)]\} = \max_a \sum_s p_s u[c(a, s)]$$

[1] We assume that fire crews have no alternative work (fuel management or trail maintenance, for example) available on idle days. Therefore, all of the crew's wage costs on idle days must be considered in cost calculations. Idle-day costs are, however, lower than wage costs on wildfire suppression days. This is because crews often work as many as sixteen hours a day while fighting fires but are typically only paid for eight hours on idle days. For a more complete discussion of crew costs see Donovan (2005). In addition, see Prestemon and Donovan (2008) for results using two other idle-day cost assumptions.

where the dot indicates the expectation with respect to the subjective probability of state s, which we call p_s.

Assuming that an economic agent understands completely the consequences of each decision given a future state, the utility-maximizing choice, a_0, depends on the subjective probabilities, p_s. Updated knowledge (information) of the probabilities of future states would be expected to enhance utility. Define $p_s = p_{s,0} = p_s(\Omega_0)$ as the probability of each future state based on a base level of information, Ω_0, and $p_{s,1} = p_s(\Omega_1)$ as the probability of occurrence of state s under an alternative information set, Ω_1. In the context of the crew-hiring problem, $p_{s,0}$ could be based on the average historical probability of state s occurring, whereas $p_{s,1}$ could be conditional likelihoods of each state, that is, based on a forecast. The utility-maximizing actions taken under each are defined as a_0 and a_1, so that the change in the expected utility, V, provided by Ω_1 compared to Ω_0, is

$$(2) \qquad V_1 = E\{u[c(a_1, \cdot)]\} - E\{u[c(a_0, \cdot)]\} = \max_a \sum_s p_{s,1} u[c(a, s)] - \max_a \sum_s p_{s,0} u[c(a, s)].$$

As defined above, the utility level, u, is dependent on the consequences, $c(\bullet)$, of the choice of a, a_0. In the context of the crew-hiring problem, define the cost-minimizing choice of agency crews as a and the consequence of this choice as $c(\bullet)$. The consequence is determined by the probabilities of the M future states, $\mathbf{p}_{s,\bullet} = (p_{1,\bullet}, p_{2,\bullet}, \ldots, p_{M,\bullet})'$. If we define R as the cost of crews, then the cost reduction obtained by utilizing Ω_1 compared to Ω_0 is

$$(3) \qquad V_{1,0} = E\{R[c(a_0, \cdot)]\} - E\{R[c(a_1, \cdot)]\} = E(R_0) - E(R_1).$$

Thus, $V_{1,0}$ can be considered the expected value of the information about the season's crew demands contained in the conditional probabilities, Ω_1, compared to the information provided by the average historical probabilities, Ω_0.

Given perfect foresight about total crew demand for each period of the approaching fire season, one state has unit probability and all other states have zero: $\mathbf{p}_* = (0, \ldots, 0, 1, 0, \ldots, 0)'$. Given $\mathbf{p}_*$, it is straightforward to identify the cost-minimizing number of agency crews to hire at the beginning of the fire season, a_*, representing a season cost of R_*. The difference between R_*, and $E(R_0)$ is the expected value of perfect foresight about the season's periodic crew demands relative to that contained in the average historical probabilities:

$$(4) \qquad V_{*,0} = E\{R[c(a_0, \mathbf{p}_*)]\} - R_*[c(a, \cdot)] = E(R_0) - R_*.$$

Similarly, the difference between $E(R_1)$ and R_* is the expected value of perfect foresight compared to the conditional probabilities embodied in Ω_1:

$$(5) \qquad V_{*,1} = E\{R[c(a_1, \cdot)]\} - R_*[c(a, \mathbf{p}_*)] = E(R_1) - R_*.$$

If the information contained in Ω_1 is more valuable than that contained in Ω_0, then $V_{*,1} < V_{*,0}$.

In research that quantifies the value of weather forecasts, average weather states ("climatology") are passed through a transfer function, resulting in an action a_0, yielding an outcome $E(R_0)$; these are then compared with the outcome, $E(R_1)$, obtained by inserting forecast weather states into the transfer function and taking an action a_1. In the method that we propose here, we instead use historical information to identify the time series of perfect-foresight cost-minimizing agency crew hires for each fire season. We then develop statistical models to predict the perfect-foresight agency crews hired. Upon estimation, we obtain a statistical model that provides a time series of predicted cost-minimizing choices, $\hat{a}_*$. The statistical models, rather than using forecasts of a single weather state and passing them through a transfer function to identify an action, instead predict the cost-minimizing action using variables that are available and known with certainty *ex ante*. Inserting the time series of $\hat{a}_*$ into Donovan's (2006) model allows us to calculate the total crew costs for the agency, $\hat{R}_*$. The value of the proposed strategy in terms of crew costs can be compared to one based on historical wildfire conditions:

$$(6) \qquad \hat{V}_{*,0} = E\{R_0[c(a_0, \mathbf{p}_0)]\} - R[c(\hat{a}_*, \mathbf{p}_*)] = E(R_0) - \hat{R}_*.$$

Empirical Application

The empirical application is for $T = 25$ fire seasons ($t = 1, \ldots, 25$), 1980–2004, in USFS Region 6 (Pacific Northwest).[2] Crew demand data were obtained from a database called Cheetah2 (Fire Program Solutions 2006), which contains data on all fires that burned in Region 6 from 1980 to 2004. We input data on the number of crews that were historically sent to fires of different sizes, and the program outputs data on crew demand. We assumed a fourteen-week fire season, which we divided into seven periods of two weeks each (the length of a typical deployment to a fire). Therefore, crew demand consisted of seven numbers (integer values) for every year. The Donovan model can be used as a two-stage decision tool, using average historical crew demands as the forecast variable. However, it can also be used to generate a time series of perfect-foresight decisions, which we then use in the development of the statistical model for a single-stage approach.

Identification of a statistical model to use to forecast the perfect-foresight hiring decision (a_*) begins by acknowledging the underlying driver of crew demand: wildfire activity. Variables that could influence wildfire activity are selected from among available measures shown by others to be related to wildfire. Regressors chosen include measures of drought, ocean temperatures, sea level pressures, and hurricane activity (Latif and Barnett 1994; Cayan et al. 1998; Nigam, Barlow, and Berbery 1999; Westerling et al. 2002, 2003; National Oceanic and Atmospheric Administration 2007). Specifically, drought measures include quarterly lags of the Palmer Drought Severity Index (National Oceanic and Atmospheric Administration 2006a) (e.g., Westerling et al. 2002, 2003), the average value of the October (previous year)-to-February (current year) Niño-3 sea surface temperature anomaly (National Oceanic and Atmospheric Administration 2006b),[3] selected monthly observations of previous year's values of the Southern Oscillation Index[4] (National Oceanic and Atmospheric Administration 2006c), the Arctic Oscillation (National Oceanic and Atmospheric Administration 2006d), the Pacific Decadal Oscillation (National Oceanic and Atmospheric Administration 2006e), and an index of Accumulated Cyclonic Energy (Landsea 2006; National Oceanic and Atmospheric Administration 2006f) for the previous year in the Atlantic Basin.

A long list of potential lags of all of these climate and drought measures is available, but observations are limited. Model selection is done with a general-to-specific strategy of starting with just two or three lags of each measure, and then dropping all variables with p-values greater than 0.15. When making forecasts of crew demands using the Poisson model parameter estimates, the forecast value is generated with a cross-validation (jackknife) approach: estimating the final model specification without the forecast year included and then forecasting the expected value for the missing year. The result of cross-validation is a time series of cross-validated forecasts of cost-minimizing agency crews, $\hat{a}_*$, and their associated costs, $\hat{R}_*$, 1980–2004.

Alternative Approaches

In addition to the single-stage statistical approach, we report results from three alternative approaches to decision making. First, we implement the two-stage approach to agency crew hires demonstrated by Donovan (2006). This involves using the simple average of the previous ten years of crew demands as the forecast of future demand conditions. For the years 1980–89, we use crew demand from 1980–90 with the relevant year excluded. The outcome of using this two-stage approach is a time series of total crew costs, R_0, that can be compared with the crew costs generated using the single-stage approach, $\hat{R}_*$.

Another comparison to the single-stage method is actual agency-hiring decisions. We requested and obtained from the Forest Service a time series of actual agency crews hired in each season in 1997–2004, a_g. Using that, we tally the cost of those hires, R_g, given the observed $\mathbf{p}_*$.[5]

[2] See Prestemon and Donovan (2008) for results from USFS Region 3 (Southwest).

[3] Tests of direct forecasts of the March-to-September average of the Niño-3 sea surface temperature anomaly (Wang 2004; National Oceanic and Atmospheric Administration 2006b) did not reveal significant relationships, once other perhaps more relevant leading indicators of ENSO were included in the Poisson models.

[4] Months of observations on the SOI were selected to be at least three months apart and identified by examining raw correlations between the SOI for middle months of the four previous quarters of the fiscal year between cost-minimizing agency crew hires in the coming fire season.

[5] Actual agency crew hire decisions may not be based on a cost-minimization criterion. They might be based on costs but be influenced by risk aversion and hiring constraints. The difference in total crew costs incurred using a climatology-based cost minimization and those actually incurred, however, does describe the cost implications of current crew decision making.

Finally, we note that the marginal cost of over-hiring agency crews is greater than the marginal cost of under-hiring. Therefore, because the forecast of cost-minimizing agency crews using the Poisson model estimate, $\hat{a}_*$, is designed to be unbiased, we would expect that a slightly (negatively) biased forecast, say $\tilde{a}_* = \hat{a}_*(1+b)$, where b (< 0) is the bias proportion, could generate lower overall costs than $\hat{a}_*$. Using simulation methods, we identified a level of bias, b, to apply experimentally to the time series of $\hat{a}_*$.[6] From these are obtained a time series of "forced-bias" costs, $\tilde{R}_*$, which we compare with R_*, R_0, $\hat{R}_*$, and R_g.

Results and Discussion

Poisson model estimates of the perfect-foresight cost-minimizing number of agency crews for Region 6 are shown in table 1. A negative binomial version of this model was attempted, but the full model's cross-validated forecast values had poorer fit to actual observations than cross-validated values generated with the Poisson version. Nonetheless, we note that the in-sample properties of the negative binomial model estimated using the same regressors has a significant (at 1%) curvature parameter estimate. Likelihood ratio tests show that the estimated Poisson model shown in table 1 is statistically better fitting (at 1% significance) than an intercept-only null model.[7]

Crew-hiring recommendations from the Donovan model, the single-stage approach, the forced-bias single-stage approach ($b = -0.2$, whose value was established through simulation), and perfect foresight are shown in columns 2–5 of table 2. Column 6 contains an eight-year time series, 1997–2004, of actual agency hires.[8] Corresponding weekly crew costs (agency plus contract) are reported in table 3, all in constant (2006) dollars. Note that the total shown at the bottom of table 3 is the sum of the season's total crew costs × 14 to account for the number of weeks in the fire season.

The results show that the new method of forecasting outperforms all of the alternative approaches considered, implying significant potential cost savings for the agency. Recalling that the perfect-foresight hiring decision is the benchmark against which to compare alternative hiring approaches, the model that yields costs that are closest to those deriving from perfect foresight is the one that represents the greatest savings. Over the twenty-five years evaluated, total crew costs from the Donovan two-stage model are $13.07 million

Table 1. Poisson Model Estimates of Perfect-Foresight Cost-Minimizing Number of Agency Fire Crews (1980–2004), Under an Assumption that Agency Crews Have No Alternative Work on Idle Days, Forest Service Region 6[e]

Variable	Parameter Estimate
Constant	0.95***
	(0.25)
Region 6 PDSI,[a] Quarter 2_t	−0.15***
	(0.05)
Region 6 PDSI,[a] Quarter 4_{t-1}	0.14***
	(0.04)
SOI[b] August$_{t-1}$	−0.31***
	(0.07)
PDO[c] November$_{t-1}$	0.34***
	(0.07)
Niño-3 SSTA[d], October$_{t-1}$ to February$_t$ Average	−0.34***
	(0.09)
Accumulated Cyclonic Energy, Atlantic$_{t-1}$	−0.011***
	(0.002)
Named Storms, Atlantic$_{t-1}$	0.20***
	(0.03)
Log-likelihood, model	−75.92
Log-likelihood, $\boldsymbol{\beta} = (1,\mathbf{0})$	−159.75
Likelihood ratio statistic	167.65***

Note: Triple asterisk (***) indicates significance at 1% or smaller.
[a]"PDSI" is "Palmer Drought Severity Index" (hydrological index).
[b]SOI is "Southern Oscillation Index."
[c]PDO is "Pacific Decadal Oscillation."
[d]Niño-3 SSTA is the Niño-3 sea surface temperature anomaly, in degrees centigrade.
[e]A negative binomial alternative of this Model had a curvature parameter estimate of −2.50 (standard error of 0.91), which was significant at 1%.

[6] Simulations were done by estimating ordinary least squares (OLS) equations that approximated the dollar penalty associated with crew forecast errors. Two equations per assumption on idle-day costs (Prestemon and Donovan [2008]) were estimated and were done using *ex post* calculations of the cost-minimizing numbers of agency crews each year, 1980–2004, for the Forest Service Region. One equation related how the size of the dollar penalty per unit of over-predictions of the cost-minimizing number of agency crews was related to the size of the over-prediction and the cost-minimizing number of agency crews. The other equation related how the size of the dollar penalty for under-prediction of the number of cost-minimizing agency crews was related to the size of the under-prediction and the number of cost-minimizing crews. Biases were applied to the size of the over-prediction and the size of the under-prediction, and the sum of the costs of these errors was calculated for all years, 1980–2004. This was the experimental bias, b, applied.

[7] The findings are obtained for count models estimated with other assumptions on idle-day costs for Region 6 and for the single model estimated for Region 3, reported in Prestemon and Donovan (2008).

[8] There is only one time series of actual agency crew hires, applicable to all assumptions regarding idle-day costs.

Table 2. Agency Fire Crew Hires, Under an Assumption that Agency Crews Have No Alternative Work on Idle Days, Made with Alternative Modeling Approaches, Perfect-Foresight Hires (1980–2004), and Actual Hires (1997–2004), Forest Service Region 6

Season	Two-Stage Approach Agency Crew Hires ($a_{0,}$)	Single-Stage Approach Agency Crew Hires ($\hat{a}_*$)	Forced-Biased Single-Stage Approach Agency Crew Hires ($\tilde{a}_*$)	Perfect-Foresight Agency Crew Hires ($a_{*,}$)	Actual Agency Crew Hires (a_g)
1980	8	7	5	0	
1981	8	8	6	2	
1982	8	7	6	6	
1983	8	7	6	0	
1984	6	10	8	11	
1985	6	40	32	31	
1986	6	7	6	8	
1987	6	16	13	18	
1988	6	15	12	27	
1989	6	4	3	10	
1990	6	9	7	13	
1991	8	16	13	18	
1992	8	9	7	17	
1993	11	5	4	0	
1994	10	39	31	31	
1995	11	2	1	8	
1996	10	6	5	21	
1997	11	6	5	4	10
1998	8	12	10	13	8
1999	8	3	2	4	6
2000	8	4	3	2	13
2001	6	17	13	10	22
2002	8	26	21	16	34
2003	8	42	34	39	33
2004	10	12	9	11	28

(1.90%) higher than those made with the perfect-foresight hiring recommendation, the single-stage model yields costs that are $7.35 million (1.07%) higher, and the forced-bias single-stage model yields costs that are $6.08 million (0.89%) higher (table 3). This last figure represents cost savings of $6.99 million when compared to the two-stage model.

These alternative crew-hiring approaches can be compared with hires actually made for the brief period where we have data from the agency, 1997–2004. Table 3 shows that actual agency hires resulted in costs that are $3.41 million (1.54%) higher over the eight years than the costs that would have been generated with perfect foresight about crew demand. The two-stage approach is $4.22 million (1.90%) higher, the single-stage approach is $1.11 million (0.50%) higher, and the forced-bias single-stage approach is only $0.83 million (0.37%) higher than the costs obtained with perfect foresight. In other words, compared to actual hires, use of the forced-bias single-stage approach generates savings to the agency of $2.58 million.

Returns to Research

A large literature is devoted to describing the returns to agricultural research and development (Smith and Pardey 1997). Schimmelpfennig and Norton (2003) state that the main product of research in agricultural economics and social science is information, which can lead to utility enhancements in consumption or profit increases in production. The gains from research in production are typically represented as technology advances, which result in outward supply shifts (e.g., Lindner and Jarrett 1978). Production function approaches are also used, which quantify the marginal productivity of research; an initial effort was by

Table 3. Total Crew Costs, Under an Assumption that Agency Crews Have No Alternative Work on Idle Days,, with Alternative Modeling Approaches, Perfect-Foresight Hires (1980–2004), and Actual Hires (1997–2004), Forest Service Region 6 (Values in Millions of 2006 US $)

Season	Two-Stage Approach Agency Crew Hires ($R_{0,}$)	Single-Stage Approach Agency Crew Hires ($\hat{R}_*$)	Forced-Biased Single-Stage Approach Agency Crew Hires ($\tilde{R}_*$)	Perfect-Foresight Agency Crew Hires (R_*)	Actual Agency Crew Hires (R_g)
1980	0.33	0.33	0.31	0.29	
1981	0.63	0.63	0.61	0.60	
1982	0.31	0.30	0.30	0.30	
1983	0.26	0.25	0.24	0.19	
1984	0.56	0.54	0.55	0.54	
1985	1.37	1.41	1.35	1.35	
1986	5.22	5.21	5.22	5.20	
1987	3.58	3.56	3.56	3.55	
1988	1.72	1.70	1.70	1.69	
1989	2.70	2.72	2.72	2.69	
1990	2.94	2.93	2.94	2.92	
1991	0.82	0.81	0.81	0.81	
1992	1.53	1.52	1.53	1.51	
1993	0.30	0.21	0.20	0.15	
1994	5.72	5.64	5.62	5.62	
1995	1.23	1.26	1.27	1.22	
1996	4.66	4.68	4.68	4.62	
1997	0.49	0.45	0.45	0.45	0.48
1998	0.97	0.96	0.96	0.96	0.97
1999	0.80	0.79	0.79	0.78	0.79
2000	1.64	1.63	1.63	1.62	1.65
2001	3.27	3.27	3.26	3.26	3.28
2002	4.78	4.78	4.76	4.74	4.82
2003	2.84	2.69	2.70	2.68	2.70
2004	1.32	1.32	1.32	1.32	1.37
Total (×14), 1980–2004, $\$10^6$	699.98	694.29	692.99	686.91	
Change from perfect, 1980–2004, $\$10^6$	13.07	7.37	6.08		
Change from perfect, 1980–2004,(%)	1.90	1.07	0.89		
Total (×14), 1997–2004, $\$10^6$	225.62	222.51	222.23	221.40	224.81
Change from perfect, 1997–2004, $\$10^6$	4.22	1.11	0.83		3.41
Change from perfect, 1997–2004,(%)	1.90	0.50	0.37		1.54

Griliches (1964). Such gains often are biased and lead to wealth transfers (e.g., Byerlee 2000; Alwang and Siegel 2003; Moyo et al. 2007).

We use a benefit-cost (B:C) ratio to quantify the returns to adopting our single-stage model. The benefits in the numerator of this ratio are reduced crew-hiring costs, compared to those observed, and the costs in the denominator are the research and development expenses of our single-stage approach with an imposed bias. From table 3, average annual crew-hiring cost reductions from using the forced-biased single-stage model over eight years are one-eighth of (\$3.41–0.83) million, or \$0.32 million. We estimate that research involved in gathering data to develop the single-stage model for Forest Service Region 6 alone represents an initial cost of \$65,000. This is our estimate of the costs of our salaries, benefits, and supplies involved in model development. We also estimate that the annual costs, also in terms of our salaries, benefits, and supplies, of maintaining

the single-stage model (updating information on crew costs and contract crew supply specifications and re-estimation of statistical models) are $5,000.[9] We assume that the average cost reduction is maintained for ten years. Using a 7% discount rate, the net present value of expected savings over these ten years is $2.27 million. The net present value of costs of model development and maintenance over those ten years are $0.10 million. This represents a ten-year return to the research of $2.17 million and a B : C ratio of 22.4. This corresponds to an internal rate of return (IRR) of 489%. This B:C ratio compares favorably with those reported by others. For example, Cubbage et al. (2000) reported B:C ratios for fusiform rust research in the timber sector that range from 2.2 to 20.3. Seldon and Newman (1987) quantified, using a production function approach, the marginal productivity of public research in the softwood plywood industry and found a marginal IRR of 236%. Griliches (1964) found B:C ratios of agricultural research to be on the order of 13, with IRRs over 300%.

No discussion of the effects of climate on wildfire would be complete without considering climate change. The effects of climate change on fire-prone ecosystems may be profound, but they are currently poorly understood. Therefore, it would be imprudent to definitively say how climate change will affect the performance of our model. Research into how climate change may affect the various regressors in the predictive model is reported in table 2 that indicates conflicting directions of effects (e.g., Trenberth and Hoar 1997; Collins 2005; Pielke et al. 2005; Westerling et al. 2006) on the cost-minimizing number of agency crews to hire. However, a number of factors are suggestive. Consider that research has shown that climate change has already increased wildfire activity (McKenzie et al. 2004; Westerling et al. 2006) and that ocean-climate relationships point to further increases in wildfire across much of the fire-prone western United States in coming decades (Kitzberger et al. 2007). Furthermore, in Region 6, total area burned by wildfire is positively correlated with total crew demand ($\rho = 0.73$) and the cost-minimizing number of agency crews ($\rho = 0.40$). This suggests that climate change may increase both the total demand for crews and the cost-minimizing number of agency crews.

[9] The authors were careful to estimate their research time conservatively, so that these cost estimates are more likely to overestimate than to underestimate the costs of research.

To further understand the potential effects of climate change, we sorted the values in table 3 by the cost-minimizing number of crews. We found that the cost savings from using the single-stage model versus the two-stage model were twice as high for the twelve years with the highest cost-minimizing number of crews compared to the twelve years with the lowest. This suggests that, all else equal, in addition to increasing demands on suppression resources generally, including fire suppression crews, climate change may increase the returns from using our single-stage model. Intuitively, this makes sense. Contract crew unit costs increase with the number supplied, so the costs of errors associated with over-hiring in times of high fire activity are magnified.

Conclusions

Research can be conducted by governments and other organizations facing decisions dependent on uncertain future states of nature to: (*a*) develop resource-allocation decision strategies that achieve better overall outcomes for a given statistical distribution of potential future states of nature and (*b*) reduce the uncertainty about future states of nature. The first category of research involves developing tools that can more effectively accommodate uncertain future states when making *ex ante* decisions, and the second category includes the empirical assessment of the statistical distribution of future states, including development of accurate forecasts of the future state. In much research that evaluates the benefits of weather and climate forecasting in the agricultural sector, decision tools are two-stage, requiring first a forecast of weather or climate and then processing in a transfer function, producing a decision recommendation. In this article, we outline a new single-stage approach that bypasses the transfer function when making decisions. Our results show that the single-stage model yields benefits, in terms of reduced spending on fire suppression, compared to a two-stage alternative. Our results also show that in periods of higher wildfire activity, as might be expected as a result of global warming, the spending reductions accruing from the single-stage model versus the two-stage model are enhanced.

We further show that use of the new single-stage model could generate large returns for the government. The reductions in total crew expenditures, reductions that are many times

greater than the research and development costs of model development, represent potential savings that would add up over many years, saving the agency millions of dollars annually, if they were to be applied in other USFS Regions or by other fire management agencies. Similarly, if these kinds of savings are obtainable for expenditures on other inputs to wildfire suppression that involve preseason contract decisions, then the Forest Service might make more significant progress toward the goal of reducing budget uncertainties, as highlighted by the U.S. General Accounting Office (2004).

Our analysis is a first step at developing methods that can lower agency spending in wildfire suppression and quantify some of the potential gains to fire research. The single-stage statistical models of cost-minimizing agency crew hires reported here have no time trends, which may not be a valid assumption given current research. For example, Westerling et al. (2006) warn of rising costs of suppression due to climate change-induced lengthening of fire seasons and longer-burning individual fires, on average. These changes may be related to climate change and highlight the need to account for these effects when making wildfire management decisions. Existing crew-hiring approaches, for example, may not fully account for rising demands due to these kinds of background changes, especially if the existing models are backward looking and do not recognize fully these underlying trends. Unfortunately, in this study, limited observations restricted our statistical options for identifying such trends. But these considerations imply an even higher return to investing in research in this area.

Improvements in our statistical models may also come about through improvements in our understanding of climatological factors linked to wildfire activity and in advances in climate forecasting (e.g., Adams et al. 1995; Solow et al. 1998). Adams and Peck (2002) discuss how western droughts may be related to climate change and document improvements in climate forecasting, while Chen, McCarl and Hill (2002) show how improved forecasting could yield gains in the agricultural sector. Such advances could help fire management agencies achieve additional cost reductions when making many kinds of wildfire management decisions under uncertainty.

Finally, in the process of developing our forecasting models, we became aware of additional potential savings that could be achieved with little extra effort or expense to the agency. Because cost penalties from maintaining an excess supply of agency crews are higher than those from excess demands for crews, there are likely to be additional gains associated with imposing biases to the crew forecasts. We demonstrated that, at least for Region 6, a negatively biased forecast performed better on historical data than an unbiased one. We conclude, then, that one way to achieve further gains from forecasting and recommending agency crew-hiring levels in advance of the season is to identify, using simulation techniques, the level of imposed bias on the crew forecast that would be expected to minimize total crew costs. An alternative conclusion is that known asymmetric penalties for under- and over-predicting the cost-minimizing number of crews could be built directly into the crew-hiring recommendation, producing a model that is most likely to minimize costs given the asymmetric penalties.

[Received June 2007; accepted January 2008.]

References

Adams, R.M., and D.E. Peck. 2002. "Drought and Climate Change: Implications for the West." *Western Economics Forum* 1(2):1–6.

Adams, R.M., B.A. McCarl, A. Solow, K.J. Bryant, D.M. Legler, and J. O'Brien. 1995. "Value of Improved Long Range Weather Information." *Contemporary Economic Policy* 13(3):10–19.

Alwang, J., and P.B. Siegel. 2003. "Measuring the Impacts of Agricultural Research on Poverty Reduction." *Agricultural Economics* 29:1–14.

Brown, B.G., and A.H. Murphy. 1988. "On the Economic Value of Weather Forecasts in Wildfire Suppression Mobilization Decisions." *Canadian Journal of Forest Research* 18:1641–9.

Byerlee, D. 2000. "Targeting Poverty Alleviation in Priority Setting for Agricultural Research." *Food Policy* 25:429–45.

Cayan, D.R., M.D. Dettinger, H.F. Diaz, and N.E. Graham. 1998. "Decadal Variability of Precipitation over Western North America." *Journal of Climate* 11(12):3148–66.

Chen, C.-C., B. McCarl, and H. Hill. 2002. "Agricultural Value of ENSO Information Under Alternative Phase Definition." *Climatic Change* 54(3):305–25.

Collins, M. 2005. "El Niño- or La Niña-Like Climate Change?" *Climate Dynamics* 24(1):89–104.

Considine, T.J., C. Jablonowski, B. Posner, and C.H. Bishop. 2004. "The Value of Hurricane Forecasts to Oil and Gas Producers in the Gulf

of Mexico." *Journal of Applied Meteorology* 43(9):1270–81.

Costello, C.J., R.M. Adams, and S. Polasky. 1998. "The Value of El Niño Forecasts in the Management of Salmon: A Stochastic Dynamic Assessment." *American Journal of Agricultural Economics* 80(4):765–77.

Cubbage, F.W., J.M. Pye, T.P. Holmes, and J.E. Wagner. 2000. "An Economic Evaluation of Fusiform Rust Protection Research." *Southern Journal of Applied Forestry* 24(2):77–85.

Donovan, G.H. 2005. "A Comparison of the Costs of Forest Service and Contract Fire Crews in the Pacific Northwest." *Western Journal of Applied Forestry* 20(4):233–9.

——. 2006. "Determining the Optimal Mix of Federal and Contract Fire Crews: A Case Study from the Pacific Northwest." *Ecological Modeling* 194:372–8.

Fire Program Solutions. 2006. "Cheetah2 Analyzer." Available at http://www.fireps.com/cheetah2/.

Griliches, Z. 1964. "Research Expenditures, Education, and the Aggregate Agricultural Production Function." *American Economic Review* 54(6):961–74.

Johnson, S.R., and M.T. Holt. 1997. "The Value of Weather Information." In R.W. Katz and A.H. Murphy, eds. *Economic Value of Weather and Climate Forecasts*. New York: Cambridge University Press, pp. 75–107.

Landsea, C. 2006. "Frequently Asked Questions, Subject E11." Available at http://www.aoml.noaa.gov/hrd/tcfaq/E11.html.

Latif, M., and T.P. Barnett. 1994. "Causes of Decadal Climate Variability over the North Pacific and North America." *Science* 266:634–7.

Lindner, R.K., and F.G. Jarrett. 1978. "Supply Shifts and the Size of Research Benefits." *American Journal of Agricultural Economics* 60(1):48–58.

Kitzberger, T., P.M. Brown, E.K. Heyerdahl, T.W. Swetnam, and T.T. Veblen. 2007. "Contingent Pacific-Atlantic Ocean Influence on Multicentury Wildfire Synchrony over Western North America." *Proceedings of the National Academy of Sciences* 104(2):543–8.

McKenzie, D., Z.M. Gedalof, D.L. Peterson, and P.W. Mote. 2004. "Climatic Change, Wildfire, and Conservation." *Conservation Biology* 18(4):890–902.

Moyo, S., G.W. Norton, J. Alwang, I. Rhinehart, and C.M. Deom. 2007. "Peanut Research and Poverty Reduction: Impacts of Variety Improvement to Control Peanut Viruses in Uganda." *American Journal of Agricultural Economics* 89(2):448–60.

National Interagency Fire Center. 2007. "Wildland Fire Statistics: Suppression Costs for Federal Agencies." Available at http://www.nifc.gov/stats/suppression_costs.html.

National Oceanic and Atmospheric Administration. 2006a. "Climate Division: Temperature-Precipitation-Drought Data." Available at http://lwf.ncdc.noaa.gov/oa/climate/onlineprod/drought/ftppage.html.

——. 2006b. "Monthly Forecasts of the El Niño Sea Surface Temperatures and Anomalies, 1950-Present." Available at http://www.cpc.ncep.noaa.gov/products/analysis_monitoring/bulletin/figf4a.html.

——. 2006c. "Monthly Values of the Southern Oscillation Index, 1950-Present." Available at http://www.cpc.ncep.noaa.gov/data/indices/soi.

——. 2006d. "Monthly Values of the Arctic Oscillation, 1950–2006." Available at http://www.cpc.ncep.noaa.gov/products/precip/CWlink/daily_ao_index/monthly.ao.index.b50.current.ascii.table.

——. 2006e. "Monthly Values of the Pacific North American Pattern (Pacific Decadal Oscillation), 1950-Present." Available at http://www.cpc.ncep.noaa.gov/products/precip/CWlink/pna/norm.pna.monthly.b5001.current.ascii.table.

——. 2006f. "2005 Atlantic Ocean Tropical Cyclones." Available at http://www.ncdc.noaa.gov/oa/climate/research/2005/2005-atlantic-trop-cyclones.html.

——. 2007. "Monitoring Atlantic Hurricane Potential." Available at http://www.cpc.noaa.gov/products/hurricane/.

Nigam, S., M. Barlow, and E. H. Berbery. 1999. "Analysis Links Pacific Decadal Variability to Drought and Streamflow in United States." *Eos* 80(61). [pages not numbered]. Available at http://www.agu.org/eos_elec/99088e.html.

Pielke, R.A., Jr., C. Landsea, M. Mayfield, J. Laver, and R. Pasch. 2005. "Hurricanes and Global Warming." *Bulletin of the American Meteorological Society* 86(11):1571–5.

Prestemon, J.P., and G.H. Donovan. 2008. "AJAE Appendix: Forecasting Resource Allocation Decisions Under Climate Uncertainty: Fire Suppression with Assessment of Net Benefits of Research." Available at http://agecon.lib.umn.edu/.

Schimmelpfennig, G.W., and D.E. Norton. 2003. "What Is the Value of Agricultural Economics Research?" *American Journal of Agricultural Economics* 85(1):81–94.

Seldon, B.J., and D.H. Newman. 1987. "Marginal Productivity of Public Research in the

Softwood Plywood Industry: A Dual Approach." *Forest Science* 33(4):872–88.

Solow, A.R., R. Adams, K.J. Bryant, D.M. Legler, J.J. O'Brien, B.A. McCarl, W. Nayda, and R. Weiher. 1998. "The Value of Improved ENSO Prediction to U.S. Agriculture." *Climatic Change* 39(1):47–60.

Smith, V.H., and P.G. Pardey. 1997. "Sizing Up Social Science Research." *American Journal of Agricultural Economics* 79(5):1530–3.

Trenberth, K.E., and T.J. Hoar. 1997. "El Niño and Climate Change." *Geophysical Research Letters* 24(23):3057–60.

U.S. General Accounting Office. 2004. "Wildfire Suppression: Funding Transfers Cause Project Cancellations and Delays, Strained Relationships, and Management Disruptions." General Accounting Office Report GAO-04-612, June 2004.

Wang, Y. 2004. Monthly Forecasts of the El Niño (Niño-3) Sea Surface Temperatures and Anomalies, 1982–2004. Data Obtained by Special Request.

Westerling, A.L., A. Gershunov, D.R. Cayan, and T.P. Barnett. 2002. "Long Lead Statistical Forecasts of Area Burned in Western U.S. Wildfires by Ecosystem Province." *International Journal of Wildland Fire* 11:257–66.

Westerling, A.L., T J. Brown, A. Gershunov, D.R. Cayan, and M.D. Dettinger. 2003. "Climate and Wildfire in the Western United States." *Bulletin of the American Meteorological Society* 84(5):595–604.

Westerling, A.L., H.G. Hidalgo, D.R. Cayan, and T.W. Swetnam. 2006. "Warming and Earlier Spring Increase Western U.S. Forest Wildfire Activity." *Science* 313:940–3.