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Risk Preferences in Strategic Wildfire Decision Making: A Choice Experiment with U.S. Wildfire Managers

Matthew J. Wibbenmeyer,[1,†] Michael S. Hand,[2,*] David E. Calkin,[2] Tyron J. Venn,[3] and Matthew P. Thompson[2]

Federal policy has embraced risk management as an appropriate paradigm for wildfire management. Economic theory suggests that over repeated wildfire events, potential economic costs and risks of ecological damage are optimally balanced when management decisions are free from biases, risk aversion, and risk seeking. Of primary concern in this article is how managers respond to wildfire risk, including the potential effect of wildfires (on ecological values, structures, and safety) and the likelihood of different fire outcomes. We use responses to a choice experiment questionnaire of U.S. federal wildfire managers to measure attitudes toward several components of wildfire risk and to test whether observed risk attitudes are consistent with the efficient allocation of wildfire suppression resources. Our results indicate that fire managers' decisions are consistent with nonexpected utility theories of decisions under risk. Managers may overallocate firefighting resources when the likelihood or potential magnitude of damage from fires is low, and sensitivity to changes in the probability of fire outcomes depends on whether probabilities are close to one or zero and the magnitude of the potential harm.

KEY WORDS: Fire management; nonexpected utility theory; risk preferences

1. INTRODUCTION

Public land and natural resource managers in the United States are increasingly responsible for addressing threats posed by environmental disturbances and natural disasters. Wildland fire, floods, invasive species, and climate change impacts (among others) often require the involvement of public agencies to manage the likelihood that a disturbance occurs and mitigate negative consequences when an incident does occur. Wildland fire managers (and sometimes managers of floods) may also be called upon to enhance the beneficial effects while minimizing potential for large and destructive incidents. Inherent in these responsibilities is risk: outcomes of environmental disturbances and natural disasters, as well as the effectiveness of potential response strategies, are generally not known with certainty before and during an incident.[4] Managerial responses to risk, and tradeoffs between the costs and potential benefits of protecting life, property,

[1]Graduate student, Department of Economics, University of California, Santa Barbara, CA, USA.
[2]USDA Forest Service, Rocky Mountain Research Station, Missoula, MT, USA.
[3]University of Montana, College of Forestry and Conservation, Missoula, MT, USA.
[†]The research was conducted as a contractor for Collins Consulting, Missoula, MT, USA.
[*]Address correspondence to Michael S. Hand, PO Box 7669, Missoula, MT 59807, USA; tel: +406 329-3375; fax: +406 329-3487; mshand@fs.fed.us.

[4]Although responses to natural disturbances, including wildland fire, involve risk, where managers know the probability distribution for potential outcomes, and pure uncertainty, where the outcome probabilities are unknown or ambiguous, this study is confined only to manager responses to risk.

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and natural resources, are important determinants of the efficiency of government responses to natural disturbances.

In this article, we ask how public agency managers respond to risk during wildfire incidents, and whether responses to risk are consistent with strategies that would minimize the expected loss from wildland fire incidents. Although the majority of economic studies of risk preference rely on expected utility models, it is well established that individuals often make decisions that are inconsistent with expected utility theory;[(1)]) ignoring this behavior may result in biased conclusions about preferences for outcomes related to natural resources.[(2)] Yet little is known about how managers acting on behalf of public agencies respond to risk, and to what degree expected or nonexpected utility models describe their decision making under risk.

Wildland fire provides an interesting laboratory for examining public managers' risk preferences. Unlike other types of incidents to which public managers respond, wildland fire events and fire suppression efforts occur with great frequency every year. Also, wildfire managers often have greater capacity to change the likelihood and physical extent of the disturbance than do managers of other natural disturbances, such as hurricanes, earthquakes, etc., in which management responses are generally limited to mitigating consequences. Wildfire management can consume significant resources and account for large portions of public land management agency budgets. In addition, suppression costs have been rising for several decades,[(3,4)] threatening the ability of the U.S. Forest Service (USFS) to meet other objectives, such as recreation, landscape restoration, and wildlife management.[(5)]

Managerial responses to risk from wildland fire occur within a complex decision-making environment. Decisions in wildfire management are determined in part by institutional rules, regulations, and management directives,[(6)] and interactions between managers and the community can affect options available for responding to a fire.[(7)] Social and political pressure can play a role in how intensively managers respond to fires,[(8)] and managers have expressed concern that political pressures and an increasing array of policies and rules may limit options for responding to fire.[(9)] Further, the incentives faced by managers may encourage aggressive suppression and discourage consideration of the beneficial effects of wildland fire.[(10–12)]

Manager decisions also occur within a context of behavioral biases, heuristics, and risk attitudes. Recent research has demonstrated that loss aversion, discounting, and *status quo* bias are significant factors in how wildfire managers make decisions.[(13)] This finding supports a broader view that actions (and inaction) by public agency managers are subject to biases that can result in suboptimal outcomes when viewed from a social welfare perspective.[(14–15)]

This study uses responses to a choice experiment (CE) survey of fire managers to estimate risk preferences when suppression strategies involve risks to structures, watersheds, and firefighting personnel. Results indicate whether more cost-effective suppression efforts can be achieved through more efficient responses to risk, and have implications for a wide range of government responses to natural and man-made disasters and disturbances.[(16)] We anticipate that this line of research will help improve risk management efforts for natural disturbance incidents and policies designed to align manager decisions with efficient outcomes.

2. WILDLAND FIRE DECISION MAKING UNDER RISK

The current policy guidance for U.S. federal wildfire managers states: "Notwithstanding protection of life, the cost of suppression, emergency stabilization and rehabilitation must be commensurate with values to be protected."[(17)] One interpretation of this statement is that resources should be invested in wildfire management until the marginal benefits equal marginal costs.[(11)] This interpretation is consistent with models of efficient wildland fire management in which the objective is to minimize the sum of suppression costs and net value change due to fire.[(18–20)]

Efficient strategies for wildland fire management that incorporate risk have also been characterized in the literature.[(21–24)] These strategies seek to minimize the sum of expected suppression costs and net value change, and require that managers are risk neutral in their decision making. That is, efficiency in wildland fire management supposes that managers are coolly analytical decisionmakers, recalculating expected impacts of a fire when conditions change, and making proportional changes in strategy that are free from biases, risk aversion, and risk seeking. This assumption is akin to disengaging the experiential and affective mode of information processing described by Epstein[(25)] and Slovic *et al.*[(26)] in complete favor of rational and analytic processing of risk information.

2.1. Nonexpected Utility Model of Wildland Fire Management

In practice, we know that most decisions will involve a role for both analytical and affective information processing. Thus, in this study we investigate the degree to which wildfire managers are responsive to various factors affecting risk. Further, we ask whether responses to these factors are consistent with the behavior that would minimize the expected economic losses due to wildfire, or whether they are better described by expected or nonexpected utility models. In this context, expected economic loss is expressed as the probability-weighted sum of potential damage to homes and degradation of watersheds resulting from wildfire.

The majority of economic studies of risk preferences rely on an expected utility model, in which preferences over outcomes are nonlinear but preferences over probabilities are linear;[22–24] however, behavior that is inconsistent with expected utility theory is well documented. Prospect theory[1] and its allied theories rank-dependent utility theory[27] and cumulative prospect theory,[28] referred to collectively as nonexpected utility theories, allow preferences for risky decisions to be nonlinear in both outcomes and probabilities. These theories help explain the observed "fourfold" pattern of risk attitudes, wherein individuals are risk averse over low-probability losses and high-probability gains, and risk seeking over high-probability losses and low-probability gains.

Shaw and Woodward[2] argue that many decision problems in natural resource economics can be described by nonexpected utility models of choice, where the assumption of preferences that are linear over probabilities is violated due to the common importance of ambiguity and low probabilities. In the fire management context, managers face considerable ambiguity with respect to social preferences, fire probabilities, and potential fire outcomes to a variety of resources, and they must frequently consider low-probability high-consequence events. We know of only a handful of CE studies that have evaluated preferences over risky attributes using models that allow for nonlinear preferences over probabilities.[29–31] Although previous studies have examined the role of decision heuristics in wildfire management,[13,14] no study has yet provided a detailed account of wildfire manager risk preferences.

We model manager risk preferences by combining a random utility model of choices of multiattribute goods[32–34] and a nonexpected utility framework where the probability of an outcome may be weighted by individuals. A similar treatment of this type of model was developed by Hensher *et al.*[31] The basic choice that managers must make is between strategies that yield utility based on potential outcomes. Respondents were asked to choose the strategy expected of them in their professional capacity; thus, utility represents a form of professional utility.

Each strategy n can result in several potential outcomes (i) that occur with probability p. A manager receives utility $v_i(x_i|\beta)$ when outcome i occurs, where x_i is a vector of outcome characteristics and β is a vector of utility function parameters that describe preferences over x_i. Thus, the utility derived from strategy n is a function of the utility associated with each outcome and the probability that each outcome occurs, or $V_n = f(\pi(p_i), v(x_i|\beta))$, where $\pi(p_i)$ is a probability weighting function that describes how managers weight each potential outcome.

Managers choose among the menu of strategies the one where V_n is highest. In a random utility model, given an unobserved random component to choices (ε), the probability of observing a choice of strategy m is,

$$Pr\,(m = 1) = Pr\,(V_m + \varepsilon > V_n + \varepsilon)\,\forall m \neq n. \quad (1)$$

To summarize, Equation (1) describes how managers evaluate the utility associated with different outcomes by making tradeoffs between different attributes (based on the β parameter vector), how managers weight the likelihood of potential outcomes associated with each strategy (the function $\pi(p_i)$), and a decision rule for choosing among strategies.

3. ECONOMETRIC METHODS

To explore decision making under risk in the context of wildfire management, we analyze two econometric choice models. By specifying functional forms for the arguments in Equation (1), these models use observations of strategies chosen by managers (in a hypothetical wildfire incident) to relate the characteristics of each strategy to the probability of choosing a strategy. Econometric analysis is useful in this context where the model and experimental design necessitate that choices are a function of multiple attributes, and when we seek parametric estimates of utility function and probability weighting parameters. We estimate a categorical model and a probability weighting model, which provide descriptive accounts of fire manager risk preferences. The estimated models allow fire manager preferences over risky outcomes to be nonlinear over outcomes and probabilities, as in nonexpected utility theories such as prospect theory. We estimate both models using the conditional logit model of probabilistic choice, which follows directly from the random utility model of choice.[32–34]

We specify a functional form for the strategy utility function, adapted from Kahneman and Tversky,[1] as the weighted sum of the utility of each outcome:

$$V_n = \sum_i \pi\,(p_i)\,\nu(x_i). \tag{2}$$

Here, $\nu(x_i)$ is the value a manager would receive from each potential outcome i of strategy n, and $\pi(p_i)$ represents the decision weight applied to the probability of outcome i. This function can accommodate the special case where $\nu(x_i)$ is linear and $\pi(p_i) = p_i$; testing these conditions indicates whether nonexpected utility is an appropriate way of modeling wildfire manager decision making under risk.

Wildfire managers' choices among potential management strategies may vary based on the attributes of those strategies and the characteristics of the wildfires to which those strategies will be applied. For example, a wildfire manager may be less willing to select a strategy offering a lower probability of success when faced with a very threatening wildfire. Let q_k equal the probability that wildfire k reaches a single resource-at-risk (in absence of suppression efforts), and let s_n equal the probability that a given strategy will be successful in protecting that resource. The nonexpected utility provided by strategy n in scenario k can be expressed as:

$$\begin{aligned} V_{nk} &= (1 - \pi(q_k))\upsilon_{n0} + \pi_q(q_k)\pi_s(s_n)\upsilon_{n0} \\ &\quad + \pi_q(q_k)(1 - \pi_s(S_n))\upsilon_{n1}. \end{aligned} \tag{3}$$

where ν_{n0} is the value of reduced-form utility under the *status quo* (i.e., when the endowed level of the resource-at-risk is preserved), and ν_{n1} is utility when the fire event occurs (i.e., when the suppression strategy fails and the fire burns the resource-at risk). Notice that the resource can preserve its *status quo* value in two ways: the fire may fail to reach it, or the fire may reach it and the suppression strategy may be successful in protecting it.

In the context of the CE design presented in the next section, ν_{n0} and ν_{n1} each contain a vector of deterministic attributes of strategy k that occur with certainty ($\mathbf{X}_n$, which is identical for outcomes ν_{n0} and ν_{n1}). In addition, υ_{n1} accounts for the impact on utility of the probabilistic loss to the resource-at-risk (z_k, the value lost when the strategy fails and the fire damages the resource). Specifying utility as a linear function of outcome factors and utility parameters gives forms of the utility function when the event does and does not occur:

$$\begin{aligned} \nu_{n0} &= \mathbf{X}'_n\boldsymbol{\beta}, \text{ and} \\ \nu_{n1} &= \mathbf{X}'_n\boldsymbol{\beta} + z_k\delta, \end{aligned} \tag{4}$$

where δ is a typically negative parameter representing the change in utility when resource z_k is lost. After collecting terms, the random utility problem for wildland fire strategy choices becomes:

$$V_{ik} = \mathbf{X}'_n\boldsymbol{\beta} + \pi_q(q_k)(1 - \pi_s(s_n))z_k\delta. \tag{5}$$

In this study we are interested in whether managers' choices among strategies are consistent with the nonexpected utility presented in Equation (1), and the specific formulation of this model presented in Equation (4). Under the special case of expected utility theory (where $\pi(p_i) = p_i$ in Equation (1)), strategy choices would be consistent with the minimization of expected economic losses from wildfire. We follow the example of van Houtven *et al.*[29] and investigate these questions by estimating categorical and parametric probability weighting function econometric models that examine preferences over different probabilities and values-at-risk.

3.1. The Categorical Model

The categorical model describes fire manager decisions over risky outcomes through the inclusion of separate dummy variables for each combination of resource-at-risk (z_k), probability fire reaches the resource-at-risk (q_k), and probability of strategy success (s_n). Comparing the parameter estimates across different combinations of factors affecting risk can indicate whether changes in these factors result in choices consistent with minimization of expected economic loss.

Incorporating the categorical variables, the utility function estimated in the categorical model is expressed as follows:

$$V_n = \mathbf{X}_n\boldsymbol{\beta}' + \mathbf{R}_{n,k}\boldsymbol{\delta}', \tag{6}$$

where $\mathbf{X}_n$ is a vector of deterministic attributes of the fire management strategy and $\mathbf{R}_{n,k}$ is a vector of categorical variables representing all possible combinations of $(1 - s_n)$, q_k, and z_k, excepting combinations omitted as reference cases.[5] Values of q_k and z_k are scenario-specific and therefore do not vary among strategies offered to address a particular wildfire scenario. The base case for the categorical model is created by omitting all combinations of $(1 - s_n) \times q_k \times z_k$ where s_n takes its maximum value.

Estimates of the $\boldsymbol{\delta}$ parameter vector form the basis of tests of three hypotheses about sensitivity to differences in the level of value-at-risk, probability of strategy success, and probability that the fire reaches the value-at-risk.

H1: Respondents are not sensitive to changes in factors affecting risk (value-at-risk, burn probability, and probability of success).

Tests of H1 are constructed by comparing the terms in $\boldsymbol{\delta}$ across different levels of $(1 - s_n)$, q_k, and z_k while holding the other two factors constant. Define $\boldsymbol{\delta}$ as the parameter associated with the categorical variable in $\mathbf{R}_{n,k}$ with given levels of $(1 - s_n)$, q_k, and z_k. Respondent sensitivity to differences in value-at-risk across scenarios k and $k+1$ is tested by evaluating whether:

$$\delta_{s_n,q_k,z_k} - \delta_{s_n,q_k,z_{k+1}} = 0. \tag{7}$$

If the test statistic in the left-hand side of Equation (7) equals zero, then we cannot reject the hypothesis H1 that respondents are sensitive to differences in value-at-risk. Because values of δ are typically negative, given that they represent the utility of an increase in expected loss, positive values of the test statistic indicate greater aversion to selecting strategies with reduced probability of success in scenarios with greater value-at-risk. Similar statistics can be constructed across varying levels of q_k and s_n.

If managers are sensitive to value-at-risk, burn probability, and probability of success, a stronger hypothesis is that they react to changes in these variables in a manner consistent with minimization of expected economic loss.

[5]For simplicity, we present the econometric framework with one resource-at-risk; however, the choice experiment application described in the following section includes two resources-at-risk: homes and a highly valued watershed. In our results, categorical variables relevant to homes and watershed are represented by $\mathrm{H}_{s,q,z}$ and $\mathrm{W}_{s,q,z}$, respectively.

H2: As factors affecting risk (value-at-risk, burn probability, and probability of success) increase, estimated declines in the utility of a strategy are proportional to changes in calculated expected economic losses.

Define additional expected economic loss relative to the reference case as $(0.90 - s_n) \times q_k \times z_k$, because reference categories in this application are combinations of $(1 - s_n)$, q_k, and z_k where s_n equals its maximum value, 0.90. This quantity is calculated for each value of $(0.90 - s_n) \times (q_k) \times z_k$. Then the relevant test for H2, again using sensitivity to value-at-risk as an example, is:

$$\left(\frac{(0.90 - s_n) \times q_k \times z_k}{(0.90 - s_n) \times q_k \times z_{k+1})}\right) \times \delta_{s_n,q_k,z_{k+1}} - \delta_{s_n,q_k,z_k} = 0. \tag{8}$$

If the left-hand side of Equation (8) is greater (less) than zero, then the estimated utility change is smaller (larger) than the change in expected loss. This indicates that managers are less (more) sensitive to changes in value-at-risk than would be consistent with minimization of expected economic losses. Similar test statistics can be constructed for comparisons over changes in s_n or q_k, holding other factors constant.

For probability of success, which is measured in this application across more than two attribute levels, we are also interested in whether respondents value decreases in probability of success proportionally to the increases in expected loss those changes in probability of success imply. That is, we are interested in whether respondents weight changes in probability of success nonlinearly depending upon where in the probability spectrum those changes occur, consistent with nonexpected utility theory.

H3: Changes in utility relative to expected economic loss are constant across adjacent intervals of probability of success.

The relevant test over two adjacent intervals of probability of success, (s_{n-1}, s_n) and (s_n, s_{n+1}), is:

$$\left[\frac{((0.90 - s_{n-1}) \times q_k \times z_k) - ((0.90 - s_n) \times q_k \times z_k)}{((0.90 - s_n) \times q_k \times z_k) - ((0.90 - s_{n+1}) \times q_k \times z_k)}\right] \times (\delta_{s_n,q_k,z_k} - \delta_{s_{n+1},q_k,z_k}) - (\delta_{s_{n-1},q_k,z_k} - \delta_{s_n,q_k,z_k}) = 0. \tag{9}$$

Equation (9) tests whether respondents weight changes across adjacent probability of success intervals equally, after accounting for the size of those intervals. With value-at-risk and burn probability held constant, the term in brackets is the ratio of the difference in probability of success over two intervals, or $(s_n - s_{n-1})/(s_{n+1} - s_n)$. If the test statistic is greater than zero, then the change in probability from s_n to s_{n+1} is overweighted relative to the change from s_{n-1} to s_n; if the second term is greater (i.e., the test statistic is less than zero), then the s_n to s_{n+1} interval is underweighted relative to the first interval.

3.2. Probability Weighting Function Model

The probability weighting model integrates concepts from nonexpected utility theory and provides a more concise description of risk preferences among fire managers. As explained earlier, risk preferences under nonexpected utility theory comprise two functions, a value function and a probability weighting function. Accordingly, we allow preferences over probabilities to follow one of the nonlinear functional forms proposed in the experimental literature. To gain insights regarding the value function we use a simple approach that includes categorical variables to indicate the different levels of each resource-at-risk.[6] This specification can be expressed as follows:

$$V_n = \mathbf{X}_n \boldsymbol{\beta}' + w\delta_1 + w\delta_2 D_z, \tag{10}$$

where D_z is a categorical variable indicating the different levels of resource-at-risk ($D_z = 0$ *if* $z = z_k$, $D_z = 1$ *if* $z = z_{k+1}$), and:

$$w = (1 - \pi_s(s))\, \pi_q(q). \tag{11}$$

The probability weighting function w estimates separate weighting parameters for the probability of strategy success and the probability the fire reaches the resource, within the functions $\pi_s(p)$ and $\pi_q(q)$, respectively.[7] Also, two resources are at risk within the application presented in the following section. Therefore, we estimate four probability weighting functions: two probability of success weighting functions, and two burn probability weighting functions.

The probability weighting functions we estimate here are based on the single-parameter form[8] described by Prelec:[35]

$$\pi(p) = \exp(-(-\ln p)^{\gamma}). \tag{12}$$

The parameter γ in this equation controls the curvature of the probability weighting function. When $\gamma = 1$, $\pi(p) = p$. This shape implies perfect discriminability, where individuals respond to all equivalent changes in probability equally. Alternatively, as γ approaches 0, the function begins to approximate a step function, where probabilities of 0 and 1 are perceived, but all other probabilities are indistinguishable from one another. Experiments have generally found γ values between 0 and 1, which is consistent with overweighting low probabilities and underweighting high probabilities. This property, coupled with the certainty effect, results in the inverse-*S* shaped probability weighting function typically observed in experimental studies.

In addition to providing estimates of probability weighting parameters, the probability weighting model provides insight into respondents' value functions. For example, $^{(\delta_1 + \delta_2)}/_{\delta_1}$ indicates the relative value of protecting the two different levels of the resource-at-risk (z). Comparing this ratio to the ratio of two levels of z (i.e., $^{z_2}/_{z_1}$) provides a measure of the degree of curvature of respondents' value functions; risk-averse behavior is associated with concave value functions.

4. SURVEY DESIGN AND DATA COLLECTION

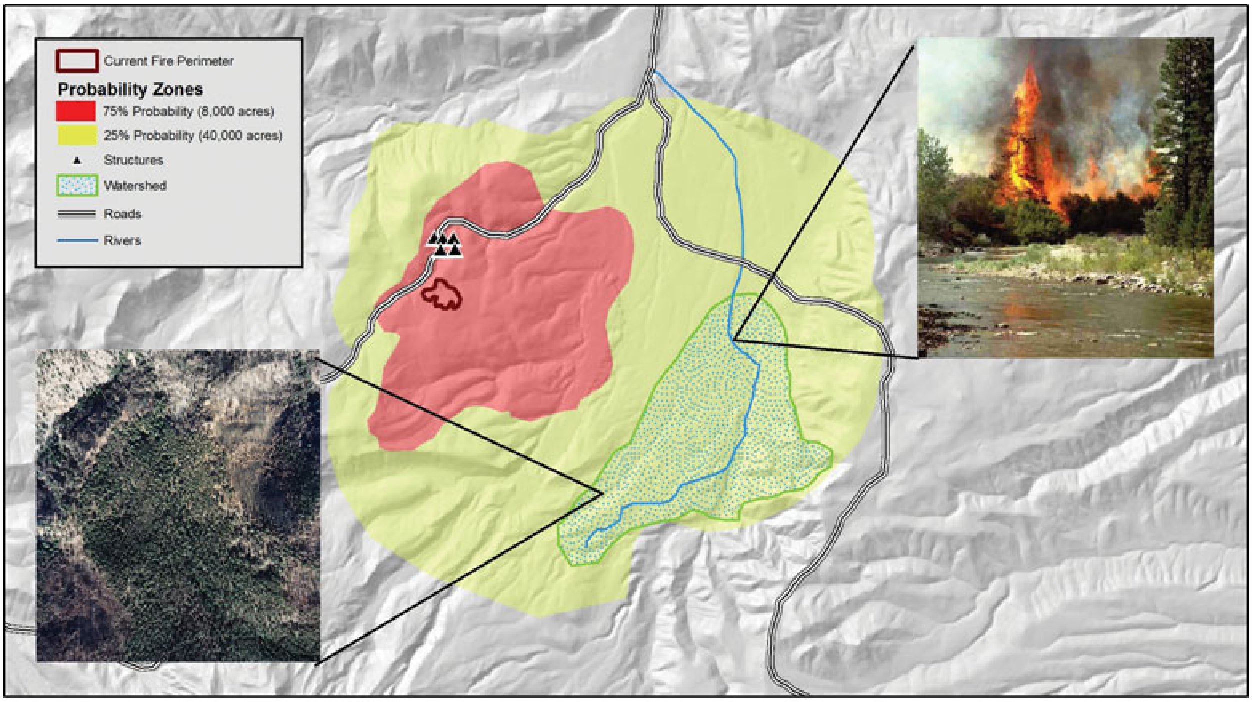
This study uses data from a web-based CE questionnaire of federal fire managers regarding their managerial preferences toward hypothetical wildfire management strategies. CE is frequently used to elicit stated preference data within environmental valuation studies; in the context of this study, CE facilitates efficient collection of manager preferences within a controlled environment designed to reflect contemporary spatial risk assessment tools familiar to fire managers.

In a decision support system such as the Wildland Fire Decision Support System (WFDSS) used for fire management in the United States,[36]

[6] The resources-at-risk in this study each have only two levels, so estimating a parametric value function would not provide any additional information over estimating utility parameters for each category of the resource-at-risk variables.

[7] In the application presented in the following section two resources are at risk: homes and a highly valued watershed. Therefore, we estimate separate weighting functions w for homes and the watershed, and we estimate parameters δ_1 and δ_2 separately for homes and the watershed.

[8] Several other parametric forms for probability weighting functions have been described in the literature, including a two-parameter form from Prelec,[35] a one-parameter form from Tversky and Kahneman,[28] and a two-parameter form from Gonzalez and Wu.[51] The discrete choice experiment data used here do not provide sufficient variation in probability values to estimate two-parameter forms. Of the single-parameter forms, the one-parameter form provided by Prelec appeared to fit our data better; therefore, it is the only form presented here.



Attribute	A	B	C
Protect residential homes	√	√	√
Protect watershed	0	√	0
Personnel exposure	100 aviation person **hours**/ 3,000 person **days** direct line production	100 aviation person **hours**/ 3,000 person **days** direct line production	100 aviation person **hours**/ 100 person **days** direct line production
Wildfire duration	<14 days	>30 days	>30 days
Probability of success	50%	90%	75%
Wildfire cost	$0.5 million	$4 million	$2 million
Expected response:	☐	☐	☐
Personal preference:	☐	☐	☐

Fig. 1. Example wildfire scenario and choice set provided to respondents. Photographs within the scenario supplemented text above the scenario to indicate potential fire severity within the watershed; in this case, there is potential for moderate-severity fire. Each scenario provided to respondents was accompanied by four choice sets.

simulated fire probability contours, calculated using a predictive model of fire spread, are overlaid with spatial identification of values-at-risk. Fire managers are then asked to consider suppression strategies and the probabilities they will be successful in containing the fire. Correspondingly, we elicited managerial preferences toward wildfire suppression strategies using a two-tiered experimental design consisting of fire scenarios and strategies. Questionnaires asked managers to respond to a series of choice sets, which presented potential strategies that could be used to manage the fire described in the associated hypothetical wildfire scenario. An example wildfire scenario and choice set are provided in Fig. 1. Each questionnaire consisted of three wildfire scenarios describing varying levels of risk to a valued watershed, and asked

Table I. Definitions and Levels of Scenario- and Strategy-Specific Attributes

Attribute	Definition	Levels
Scenario attributes		
*h*30	30 homes (value of $200,000 on average) are at risk.	= 1 if yes; = 0 if no. If no, then 5 homes are at risk.
q_h	Probability fire will reach homes in absence of suppression efforts.	0.25; 0.75
mod	The highly valued watershed has medium tree density, although the riparian zone along the river illustrated has high tree density. Mixed severity in nonriparian areas and high-severity fire in the riparian area is projected.	= 1 if yes; = 0 if no. When the watershed is at risk for high severity fire, it is not at risk for moderate severity fire.
high	The highly valued watershed has high tree density throughout, including in the riparian zone. High-severity wildfire in nonriparian areas and in the riparian area is projected.	= 1 if yes; = 0 if no. When the watershed is at risk for moderate severity fire, it is not at risk for high severity fire.
q_{ws}	Probability fire will reach the watershed in absence of suppression efforts.	0.25; 0.75
Strategy attributes		
hprotect	Strategy protects homes.	= 1 if yes; = 0 if no.
wsprotect	Strategy protects the watershed.	= 1 if yes; = 0 if no.
probsucc	Probability of success if a strategy that protects homes or the watershed is chosen.	0.50; 0.75; 0.90
aviation	Aviation person-hours.	50; 100; 1,000
ground days	Direct line person-days.	0; 100; 3,000
duration	Wildfire duration.	<14 days; >30 days
cost	Wildfire management cost.	\$0.2 million; \$0.5 million; \$2 million; \$4 million; \$8 million; \$15 million

respondents to select a strategy from each of four choice sets associated with each scenario. Attributes used in the CE questionnaire are defined as either scenario-specific or strategy-specific, and definitions and levels used for each attribute are provided in Table I.

Scenarios described the current perimeter of a hypothetical wildfire and its 0.75 and 0.25 burn probability contours (likelihood of a fire reaching a given extent projected over the next 14 days, provided the fire is not suppressed). Located within the burn probability contours (which were drawn consistently across scenarios), each scenario contained two values-at-risk: a highly valued watershed and a group of homes. We varied levels of risk to these attributes by varying the number of homes at risk (5 or 30 homes) and the potential wildfire severity within the watershed (moderate or high severity), and by varying the locations of homes and the watershed relative to the reported fire probability contours. Using an experimental design, we selected 12 wildfire scenarios, which described different levels of risk to homes and the highly valued watershed, to present to respondents.

The choice sets accompanying scenarios asked respondents to select from three alternative fire management strategies the "strategy that you believe best meets community, agency leadership and political expectations, and conforms to federal fire and land management policies."[9] Strategy attributes included

[9]Respondents were asked to indicate the management strategy they expected they would pursue in the field. In addition, respondents were separately asked to indicate a "preferred" strategy, or "the strategy you believe would result in the best long term fire management outcomes, ignoring community, agency leadership and political expectations." In this study, we only report models using expected strategy as the dependent variable. (A comparison of expected and preferred responses with these survey data can be found in Calkin *et al.*[(52)]) Expected management strategy selections are more likely to reflect the actual choices managers would make, and thus are more relevant to fire management outcomes. The models of expected strategy choices also had substantially better goodness of fit than models of preferred strategy choices, and tests of responses to risk with preferred responses yielded highly inconsistent results. For the probability weighting

suppression cost, expected fire duration, personnel exposure to hazard, and risk to homes and the highly valued watershed. Definitions and levels for "Wildfire cost" (*cost*), "Wildfire duration" (*duration*), and "Personnel exposure" (*aviation* and *ground days*), which were described as deterministic attributes of fire management strategies (components of $\mathbf{X}_n$), are given in Table I.

Risk to the homes and watershed was described probabilistically based on the chosen strategy's probability of success and the base level of risk described by the resources' locations relative to the fire probability contours. Each management strategy was described as providing protection to homes, the watershed, both, or neither; resources protected by each strategy were indicated by the variables "Protect homes" (*hprotect*) and "Protect watershed" (*wsprotect*). Second, management strategies were described as succeeding with a probability given by the attribute "Probability of success" (*probsucc*). For example, if the management strategy protected the watershed, but not homes, and had a probability of success of 0.75, the strategy would have a 0.75 probability of protecting the watershed, but zero probability of protecting homes. Therefore, we define probabilities of success with respect to homes (s_h) and the watershed (s_{ws}), respectively, as:

$$s_h = probsucc \times hprotect, \quad \text{and} \tag{13}$$

$$s_{ws} = probsucc \times wsprotect. \tag{14}$$

In addition, on the basis of the location of resources relative to fire probability contours, there would be either 0.25 or 0.75 probability (q_k) that the fire never reached the homes (or the watershed), even without protection. This two-tiered design, in which risk enters in both tiers, adds a level of complexity absent in other studies of risk preferences; therefore, analyses of managerial risk preferences are somewhat more involved. Due to the complexity, however, we are able to test reactions to various components and levels of risk that are salient to the actual sources of risk fire managers must consider in evaluating various management strategies.

We designed and administered the survey in a web-based questionnaire following best-practice procedures described in the environmental choice modeling literature.[37,38] We held a focus group in Missoula, MT to allow fire managers to provide input into the survey design. Later, at a national fire conference, we pretested the questionnaire with a group of fire managers to suggest areas where it might be improved. Beginning in March 2009, the survey was administered to agency administrators within the U.S. Forest Service (district rangers and forest supervisors, all of whom have fire management authority) and fire and fuels management professionals (including U.S. Forest Service Fire Management Officers, Assistant Fire Management Officers, and federal land management agency personnel who had completed higher level courses in fire management decision making administered by the National Wildfire Coordination Group). In total, we sent 2,054 federal fire managers e-mails asking them to complete the web-based questionnaire.

5. RESULTS

We received a total of 583 completed surveys, resulting in an overall response rate of 28.4%.[10] Table II summarizes several characteristics of the sample. The sample primarily consists of Forest Service managers with significant experience and/or some level of seniority within the federal land management agencies. We specifically targeted fire managers who have decision-making authority, either in the formulation or execution of fire management plans. Agency administrators (generally district rangers or forest supervisors who are responsible for developing suppression strategies and objectives consistent with existing fire and land management plans) comprise 37.7% of the sample, whereas 37.9% of the sample was made up of fire or fuels management professionals (those specifically engaged in fire

function model, the preferred strategy model estimates generally failed to converge.

[10] Our response rate is within the range, although on the low end, of typical response rates found in other studies of similar survey methods, for example, between 22% and 79% for general population surveys;[53] between 20% and 60% for contingent valuation surveys;[54] and between 28% and 86% in a meta-analysis of survey nonresponses.[55] Wilson *et al.*[13] obtained a response rate of 34% with a similar target population. Despite a reasonable response rate, the possibility remains that respondents are not representative of the target population, and that nonrespondents have different risk attitudes and preferences. Due to the narrow time frame for conducting the survey (when managers are preparing for the fire season, but before they are in the field), a nonresponse survey was not conducted. Thus, conclusions may not be representative of all fire managers. Ongoing research using a more recent survey of fire managers specifically designed a nonresponse survey into the sample contact plan to more fully account for potential nonresponse bias and representativeness.

Table II. Respondent Characteristics

	Count	Percent		Count	Percent
Gender			Experience		
Male	451	77.40%	0–4 years	7	1.2%
Female	132	22.60%	5–9 years	30	5.1%
Total	583	100.00%	10–14 years	45	7.7%
			15–19 years	77	13.2%
Current federal grade level			20–29 years	239	41.0%
5–6	13	2.20%	30+ years	185	31.7%
7–8	45	7.70%	Total	583	100.0%
9–10	50	8.60%			
11–12	202	34.60%	Agency		
13–15	270	46.30%	Forest Service	495	84.9%
SES[a]	1	0.20%	Bureau of Indian Affairs	5	0.9%
Other	2	0.30%	Bureau of Land Management	13	2.2%
Total	583	100.00%	National Park Service	69	11.8%
			Interagency	1	0.2%
			Total	583	100.0%

[a]Senior Executive Service, a pay schedule series including most managerial, supervisory, and policy positions above General Schedule grade 15.

management). The remainder of the sample consisted of individuals who are not currently in a fire management position, but have completed advanced fire management training and likely maintain some role within fire and fuels management.

5.1. Categorical Model Results and Tests

Table III provides parameter estimates from the categorical model. Coefficients on each of the categorical variables provide estimates of losses to managerial utility when probability of success with respect to homes or the highly valued watershed is reduced from 0.90 (the reference case) to the specified amount, given the base level of risk described in the associated wildfire scenario. Tests applied to these estimates can be used to investigate whether managers are sensitive to various components of risk (hypothesis 1), and whether the degree of sensitivity to various components of risk corresponds with minimization of expected economic loss (hypotheses 2 and 3).

Tests of hypotheses 1 and 2 are presented in Figs. 2 and 3, respectively. In both figures, panel A presents tests of sensitivity to burn probability and values-at-risk, whereas panel B presents tests of sensitivity to probability of success. In each figure, markers for tests with respect to homes are unfilled and markers for tests with the respect to the watershed are filled.

Fig. 2 presents tests of hypothesis 1, which supposes that managers are sensitive to the various components of risk. Test statistics with respect to homes in Fig. 2(A) (tests of H1 with respect to burn probability and values-at-risk) are generally significantly different from zero and positive, indicating that managers are more averse to the prospect of diminished probability of success when more homes are at risk and when burn probability is greater. For watersheds, respondents were less inclined to select strategies with lower probability of success when the watershed was within a higher burn probability contour or was at risk of high-severity fire. Respondents were generally averse to strategies with reduced probability of success for both homes and watershed, as indicated by Fig. 2(B); however, they displayed a peculiar preference for strategies with 0.50 probability of success for watersheds. These tests reject hypothesis 1 and provide evidence that managers were attentive to differences in risk factors across scenarios.

Hypothesis 2, tests of which are presented in Fig. 3, examines the stronger hypothesis that choice behavior was consistent with choices that would minimize expected economic losses. That is, did managers respond to a change in a factor affecting risk proportionally to the change in expected economic loss? With a few exceptions, these tests reject hypothesis 2.

Fig. 3(A) indicates that managers did not respond to increases in burn probability or the number of homes at risk as strongly as would be predicted

Table III. Categorical Model Results: Conditional Logit

Variable	Coeff.	*SE*
aviation	1.10E-05	1.23E-04
ground days	5.58E-05***	1.92E-05
duration	−0.0226***	0.0032
cost	−0.0256**	0.0106
$H_{s = 0.75, q = 0.25, z = 5}$	0.1167	0.0974
$H_{s = 0.50, q = 0.25, z = 5}$	−0.7045***	0.1050
$H_{s = 0, q = 0.25, z = 5}$	−1.5990***	0.1168
$H_{s = 0.75, q = 0.75, z = 5}$	−0.0347	0.0896
$H_{s = 0.50, q = 0.75, z = 5}$	−0.9117***	0.0907
$H_{s = 0, q = 0.75, z = 5}$	−2.1840***	0.1258
$H_{s = 0.75, q = 0.25, z = 30}$	−0.1295	0.0999
$H_{s = 0.50, q = 0.25, z = 30}$	−1.0140***	0.1065
$H_{s = 0, q = 0.25, z = 30}$	−2.0410***	0.1244
$H_{s = 0.75, q = 0.75, z = 30}$	−0.1805	0.1186
$H_{s = 0.50, q = 0.75, z = 30}$	−1.4690***	0.1254
$H_{s = 0, q = 0.75, z = 30}$	−2.7910***	0.1875
$W_{s = 0.75, q = 0.25, z = mod}$	−0.5331***	0.1991
$W_{s = 0.50, q = 0.25, z = mod}$	0.1559	0.1749
$W_{s = 0, q = 0.25, z = mod}$	−0.6681***	0.1245
$W_{s = 0.75, q = 0.75, z = mod}$	−0.4317***	0.1674
$W_{s = 0.50, q = 0.75, z = mod}$	0.0575	0.1519
$W_{s = 0, q = 0.75, z = mod}$	−0.9784***	0.1072
$W_{s = 0.75, q = 0.25, z = high}$	−0.6219***	0.1812
$W_{s = 0.50, q = 0.25, z = high}$	0.1141	0.1615
$W_{s = 0, q = 0.25, z = high}$	−0.9756***	0.1155
$W_{s = 0.75, q = 0.75, z = high}$	−0.7837***	0.1797
$W_{s = 0.50, q = 0.75, z = high}$	−0.2243	0.1590
$W_{s = 0, q = 0.75, z = high}$	−1.3540***	0.1148
No. of obs.	19575	
No. of pars.	28	
Log-Likelihood	−5782.7	
Pseudo R^2	0.1930	

Note: *** and ** indicate *p* values of 0.01 and 0.05, respectively.

under expected loss minimization. For instance, holding burn probability constant, the loss in utility resulting from a decrease in probability of success from 0.90 (the reference case) to 0.50 was less than six times greater when 30 homes were at risk than when 5 homes were at risk. Similarly, responses to burn probability for watersheds are not as strong as would be predicted under expected loss minimization when probability of success is held constant at 0.75 or 0. (Because watershed fire severity is a qualitative measure, calculations of expected loss with respect to changes in severity cannot be calculated numerically.)

Fig. 3(B) shows that, with respect to homes, respondents overweighted decreases in probability of success from 0.90 to 0.50 relative to decreases from 0.90 to 0.75, and decreases from 0.90 to 0 relative to decreases from 0.90 to 0.50. For watersheds, respondents underweighted decreases in probability of success from 0.90 to 0.50 relative to decreases from 0.90 to 0.75, and they overweighted decreases from 0.90 to 0 relative to decreases from 0.90 to 0.50.

Fig. 4 presents tests of hypothesis 3, which asks whether relative probability weighting across adjacent probability intervals is constant. For homes, respondents underweighted changes in probability of success from 0.90 to 0.75 relative to changes from 0.75 to 0.50, but they overweighted changes in probability of success from 0.75 to 0.50 relative to changes from 0.50 to 0. Similar results were exhibited for watersheds, although the pattern of weighting was reversed and more difficult to interpret given the anomalous response to watershed risk when the probability of success was 0.50 (see Fig. 2A). Overall these test statistics reject hypothesis 3, indicating nonlinear responses to changes in risk factors.

5.2. Parametric Probability Weighting Results

To provide additional detail regarding fire managers' risk preferences, we estimated a probability weighting model based on Equations (9) and (10), the results of which are provided in Table IV. This model is derived from nonexpected utility theory; therefore, it provides estimates of parameters that summarize sensitivity to probability and the value (or utility) function. Coefficients on w_h and $w_h \times h30$ can be interpreted as indicative of respondents' value function with respect to homes. Under the null hypothesis that managers minimize expected economic losses (i.e., a linear value and probability weighting functions), the coefficient on $w_h \times h30$ is expected to be five times larger than the w_h coefficient, corresponding to the 25 additional homes-at-risk when $h30$ is equal to 1; however, the $w_h \times h30$ coefficient is less than the coefficient on w_h. Although there is no relevant quantitative measure of expected loss associated with moderate- and high-severity fire within the highly valued watershed, the value function appears to be similar to that observed for the attribute homes: any fire within the watershed causes utility loss, and the added loss associated with high-severity fire is somewhat smaller.

Probability of success and burn probability are each weighted separately for homes and watershed; therefore, Table IV contains four γ values, and the probability weighting functions implied by these parameter estimates are illustrated in Fig. 5. The γ values representing probability weighting on burn probabilities for homes and watershed are similar and

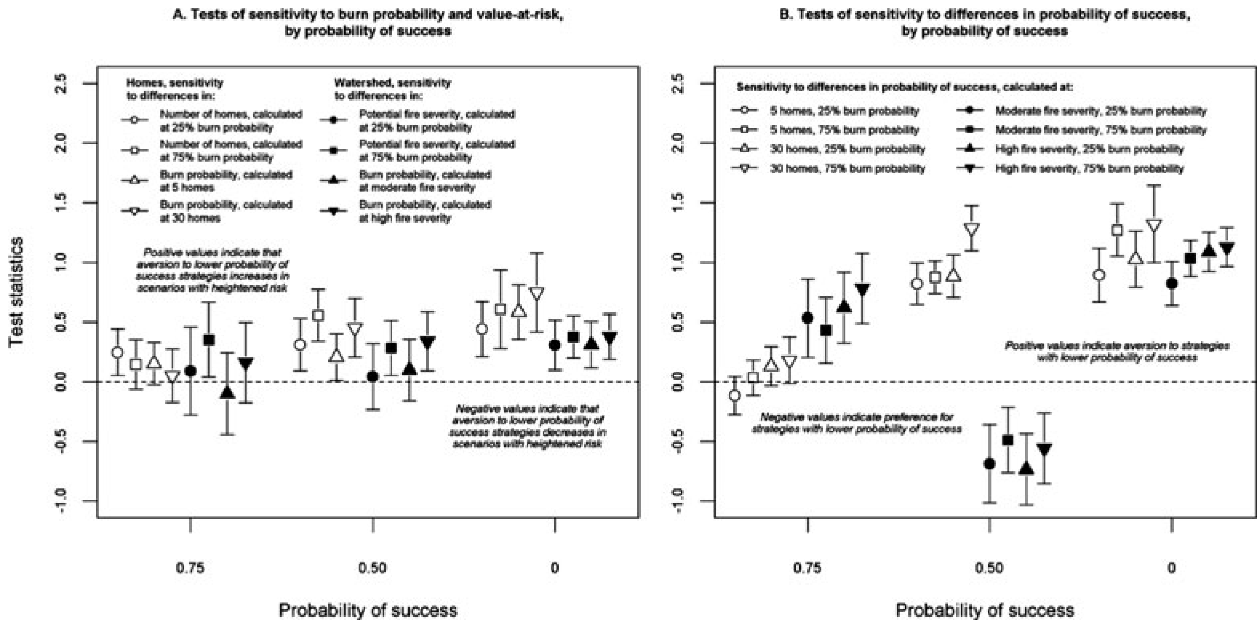


Fig. 2. Tests of sensitivity to changes in factors affecting risk (hypothesis 1, Equation (7)).

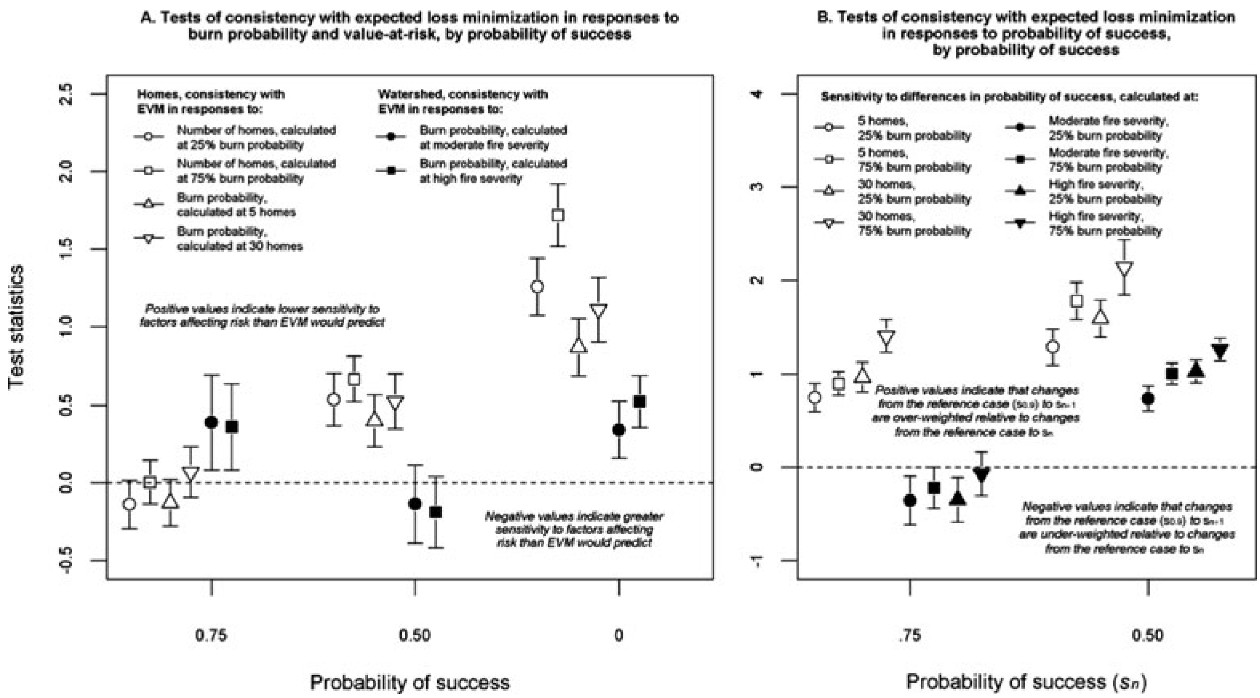


Fig. 3. Tests of consistency with expected loss minimization (hypothesis 2, Equation (8)).

relatively low. Values around 0.20 indicate that respondents substantially underweight the significance of differences across burn probabilities; in other words, they are insensitive to differences across burn probabilities. The estimated γ value for probability of success with respect to homes is greater than 1, indicative of an *S*-shaped probability weighting function. The γ value estimated for probability of success with respect to the watershed is not significantly different from zero, though this result is no doubt

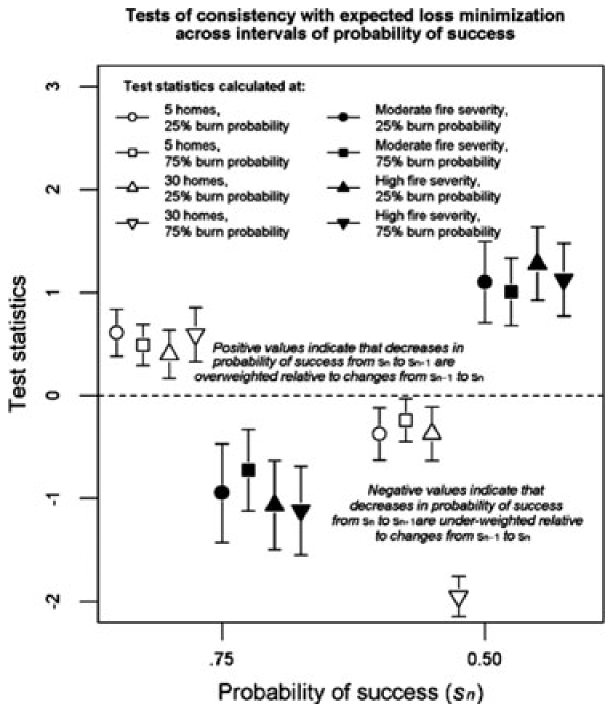


Fig. 4. Tests of consistency with expected loss minimization across adjacent probability of success intervals (hypothesis 3, Equation (9)).

influenced by unexpected responses to strategies with 50% probability of success with respect to the watershed.

6. DISCUSSION

The effects of natural disturbances, including wildfire, are often directly tied to the actions and attitudes of government agencies tasked with assessing and responding to large-scale risks. Theory suggests that over a large portfolio of wildfire events (or other types of natural disturbances), efficient outcomes will be realized when managers minimize the expected losses from each event, and federal wildland fire management policy appears to support this view. However, results from this study indicate that the risk preferences of wildfire managers when selecting suppression strategies are inconsistent with behavior that would minimize expected economic loss. Results are broadly consistent with other findings related to fire manager decision making, particularly research by Wilson *et al.*[13]

When choosing among strategies, managers appear to weight the probability of damage based in

Table IV. Probability Weighting Model Results: Conditional Logit

	Param. Estimate	*SE*
Coeffs. *Aviation*	$1.94E-05$	$1.14E-04$
Ground days	$1.99E-05$	$1.78E-05$
Duration	-0.0198^{***}	0.0029
Cost	-0.0356^{***}	0.0102
w_h	-5.4135^{***}	0.2597
$w_h \times h30$	-1.4377^{***}	0.2827
w_{ws}	-5.1343^{***}	0.4738
$w_{ws} \times high$	-1.3992^{***}	0.3522
Probability weighting pars.		
$\gamma_{s,h}$	1.4325^{***}	0.2092
$\gamma_{q,h}$	0.2021^{***}	0.0352
$\gamma_{s,ws}$	0.0273	0.0578
$\gamma_{q,ws}$	0.1970^{***}	0.0484
No. of obs.	19620	
Log-likelihood	-5806.4	
No. of pars.	12	

Note: *** indicates *p* values of 0.01.

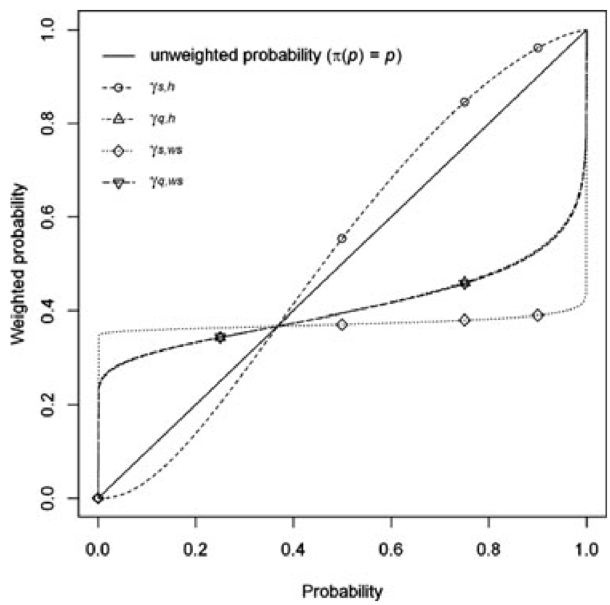


Fig. 5. Probability weighting functions implied by γ values estimated in probability weighting model.

part on the source of probability variation; with respect to homes, manager choices were more sensitive to differences in the probability of success than to burn probability. One possible explanation for this difference (summarized by the substantial difference between estimates of the probability weighting parameters $\gamma_{s,h}$ and $\gamma_{q,h}$) is the isolation effect, suggested by Tversky.[39] The isolation effect suggests that individuals discount characteristics shared by alternatives within a choice set and inflate the importance of characteristics that differentiate them. That is, managers may have felt they had no control over fire scenarios but could control the probability of success within their chosen strategy.

Managers were more sensitive to changes in the probability of success over moderate probabilities than to changes over relatively high probabilities. This pattern is characteristic of an *S*-shaped probability weighting function rather than the inverse *S*-shape typically observed in experimental studies. Roberts *et al.*[31] also observed *S*-shaped probability weighting in the natural resource context, and compared it to the decision whether to leave home with an umbrella when there is a chance of rain: one takes the umbrella when the probability of rain is beyond some probability threshold. In the fire management context, this implies that managers are overly optimistic about strategies with a relatively high probability of success, and that they may be overly pessimistic regarding strategies with a low probability of success. Of note is that while burn probabilities can be modeled with a relatively high degree of accuracy,[40] likelihood of fire management strategy success is not well understood. Differences in probability weighting across sources of probability variation may also be partly driven by attitudes toward the accuracy of information provided in the CE questionnaire.

We found managerial responses to low levels of risk (due to low home or watershed burn probabilities, or fewer homes at risk) to be disproportionately large relative to their responses to high-risk scenarios. This observation is consistent with probability neglect (an overreaction to low-probability events because of high-affect outcomes) coupled with insensitivity to numbers (a greater response to low or initial levels of the value-at-risk, and lower marginal sensitivity to additional units of the value-at-risk) described in Slovic and Peters.[42]

Another possibility is that managers' choices exhibit an emotional response, or affect. The degree and shape of probability weighting can be explained by how affect-rich or affect-poor are the potential outcomes.[42][11] For example, damage to homes is often perceived as a devastating outcome for those affected. On the other hand, damage to watersheds is more difficult to comprehend and may not to carry the same emotional weight as homes. Thus, we may not observe the same responses to risk for both homes and watershed due to greater affective content of homes.

Although the survey was not designed to specifically test for the role of affect, the results also raise the question of how managers (and others) weight probabilities when multiple attributes are at risk and have different affective content. Our results suggest, for example, that managers make tradeoffs between potential damage to homes and watershed, and managers weight the risk to these attributes differently. An open theoretical and empirical question, then, is how affect and risk attitudes relate to preferences (i.e., utility functions) for multiple attributes, which builds on multiattribute utility theory and multicriteria decision analysis with uncertainty.[43,44]

A practical implication of these findings is that we do not know if choices made by managers, even when they deviate from strategies that would minimize expected losses, reflect broader social preferences. Experimental evidence has shown that risk attitudes of managers may not deviate greatly from risk attitudes of the general public,[45] but it is not known if this result would hold when multiple attributes are at risk or in a fire management context.

Our results imply significant potential for improved risk management in wildfire suppression decision making. In particular, it appears that more efficient allocations can be realized if managers choose strategies that use fewer resources for fires that present relatively little risk. Restraining the commitment of suppression resources on low-risk incidents could reduce personnel exposure to risk and suppression expenditures, and allow for more flexibility in allocating appropriate resources to fires during times of high fire activity. Given the emerging consensus that the trend in USFS expenditures on wildfire management is unsustainable,[5] avoiding overallocations of resources to low-risk incidents may help the USFS more cost effectively meet its fire and nonfire management goals.

Although the potential exists for improved risk management of wildland fires, this is not a trivial task. First, institutional constraints and incentives are a barrier to improvement. For example, the decision to use wildland fires to attain beneficial resource impacts, which is perceived to be riskier than the decision to aggressively suppress a fire, has in the past been shown to lack agency support.[9,36] Canton-Thompson *et al.*[9] found that fire managers felt they would receive little agency support, and might be held personally liable, if the suppression strategies they chose were ineffective. Furthermore, fire

[11]Thanks to an anonymous reviewer for pointing out this connection.

managers may not have an incentive to constrain costs because wildfire suppression activities are often funded through emergency funds and a national funding pool.[9,14,46]

Second, Calkin *et al.*[16] argued that the absence of formal risk-management training within the USFS and interagency fire training programs may impede risk-based wildfire management practices. Maguire and Albright[14] were more cautious, arguing that training may not be fully effective in mitigating decision biases because these biases have been observed even in well-trained individuals.[47] In this study, managers at higher pay grades or who had managed more fires in their career did not have significantly different risk attitudes than less experienced managers; agency administrators (separate from other fire managers) showed statistically different choice patterns with respect to risk, but generally not statistically different over- or underweighting of risk factors relative to loss-minimizing strategies.[12]

Finally, it may be necessary to consider strategy choices as allocation decisions among multiple fire events. This would require greater responsibility among higher level managers for deciding which fires receive more or fewer suppression resources (e.g., at the area or regional level) and less autonomy for incident-level managers. However, it is not known whether suppression resource allocations made by higher level managers in response to risk would be substantively different.

This study is subject to several limitations, some of which should spur further research. First, we measured fire manager risk preferences using a stated preference survey instrument; future research might explore fire manager attitudes toward risk using observational data. Also, the conclusions are limited to the target population surveyed—wildland fire managers—and we caution against extrapolating results beyond this group of respondents. Some information about incident-level decisions and risk management is available in the web-based WFDSS, although significant investments in data collection would be necessary to use this information for research purposes. WFDSS data could allow for an applied study of how the content of risk communication is related to risk attitudes, similar to experimental studies by Keller *et al.*[48]

Second, we measured preferences over a limited range of probability values and levels of values at risk, and the probabilities did not encompass values near zero or one.[13] For this reason, we interpret probability weighting results primarily as reflections of sensitivity to changes over moderate probabilities. A more comprehensive account of manager risk preferences would include attitudes toward low-probability, high-consequence events, similar to experiments using hypothetical earthquake risk,[49] or extending lottery experiments by Holt and Laury[50] to multiple attributes.

Finally, risk preferences are a single component within a large suite of decision biases and mental heuristics that may contribute to less efficient fire management outcomes; additional research on framing, discounting, *status quo* bias, and the role of incentives in contributing to these decision biases has potential to suggest possible opportunities for improving wildfire manager decision processes.

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[12] Results are available from the authors upon request. Analyses of choices by individual characteristics were limited to the categorical model (due to lack of convergence of the maximum likelihood function in the probability weighting function model). For agency administrators, responses to risk of damage to the watershed exhibited statistically different over- or underweighting for a few probability categories. In general, these responses showed less bias but still differed significantly from choices that would minimize expected losses from fire.

[13] Although we measured preferences toward strategies with zero probability of success with respect to homes and watershed, probability weights at zero are assumed to be fixed at zero. Therefore, preferences toward strategies with zero probability of success do not provide information regarding probability weights at low nonzero probabilities.

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