



## A decision-analytic approach to the optimal allocation of resources for endangered species consultation

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### ABSTRACT

The resources available to support conservation work, whether time or money, are limited. Decision makers need methods to help them identify the optimal allocation of limited resources to meet conservation goals, and decision analysis is uniquely suited to assist with the development of such methods. In recent years, a number of case studies have been described that examine optimal conservation decisions under fiscal constraints; here we develop methods to look at other types of constraints, including limited staff and regulatory deadlines. In the US, Section Seven consultation, an important component of protection under the federal Endangered Species Act, requires that federal agencies overseeing projects consult with federal biologists to avoid jeopardizing species. A benefit of consultation is negotiation of project modifications that lessen impacts on species, so staff time allocated to consultation supports conservation. However, some offices have experienced declining staff, potentially reducing the efficacy of consultation. This is true of the US Fish and Wildlife Service's Washington Fish and Wildlife Office (WFWO) and its consultation work on federally-threatened bull trout (*Salvelinus confluentus*). To improve effectiveness, WFWO managers needed a tool to help allocate this work to maximize conservation benefits. We used a decision-analytic approach to score projects based on the value of staff time investment, and then identified an optimal decision rule for how scored projects would be allocated across bins, where projects in different bins received different time investments. We found that, given current staff, the optimal decision rule placed 80% of informal consultations (those where expected effects are beneficial, insignificant, or discountable) in a short bin where they would be completed without negotiating changes. The remaining 20% would be placed in a long bin, warranting an investment of seven days, including time for negotiation. For formal consultations (those where expected effects are significant), 82% of projects would be placed in a long bin, with an average time investment of 15 days. The WFWO is using this decision-support tool to help allocate staff time. Because workload allocation decisions are iterative, we describe a monitoring plan designed to increase the tool's efficacy over time. This work has general application beyond Section Seven consultation, in that it provides a framework for efficient investment of staff time in conservation when such time is limited and when regulatory deadlines prevent an unconstrained approach.

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### 1. Introduction

Adequate time and money are not available for all proposed conservation work. Therefore, difficult resource allocation deci-

sions must be made by government agencies and conservation organizations; this fact has spawned a great deal of research intended to support decision makers. Many efforts have involved schemes for prioritizing geographic areas and/or species for conservation. Prioritization schemes have generally focused on at least one of two general concepts: vulnerability and irreplaceability (Brooks et al., 2006), where areas/species that are more vulnerable (e.g., high proportionate habitat loss, IUCN threatened status) or irreplaceable (e.g., areas with high levels of endemism, taxonomically unique species) receive higher priority.

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However, prioritization schemes have not generally involved consideration of the efficient use of limited conservation resources (Murdoch et al., 2007; Bottrill et al., 2008; Joseph et al., 2009) because costs are not explicitly factored into analyses (Brooks et al., 2006). However, the allocation of scarce conservation resources can usefully be seen as a multiple-objective decision problem (Keeney and Raiffa, 1976) where the goal is to identify the greatest conservation gain for the lowest cost (or more simply, for a given budget). The decision-analytic concept, when applied to the problem of geographic area prioritization, gives rise to optimal reserve design (examples from an extensive literature include Possingham et al., 2000; Moilanen and Cabeza, 2002; McCarthy et al., 2005; Moilanen et al., 2006; Wilson et al., 2006). The concept can also be applied to species prioritization schemes, as ably demonstrated by McCarthy et al. (2008) and Joseph et al. (2009). An analog can be found in the application of decision analysis to the conservation of individual species, where the goal is to identify optimal decisions about which of several management actions should be undertaken to conserve a single species, given resource constraints (see also Martin et al., 2007).

Decision analysis (sensu Clemen, 1996; Possingham et al., 2001) increases the effectiveness of decision-making through deconstruction and analysis of the components of a decision (i.e., management objectives, alternative actions, predictive models; Hammond et al., 1999), followed by reconstitution of those components into a framework for identification of optimal decisions. Decision analysis is especially effective for complex decisions that require simultaneous consideration of multiple management objectives and substantial uncertainty, and it recognizes that some decision elements are informed primarily by values or policy (i.e., management objectives) while others are primarily the purview of science (i.e., predictive models). Decision analysis is needed to effectively frame conservation problems to provide information most useful for decision makers (Possingham et al., 2001; McCarthy et al., 2008).

In the US, the Endangered Species Act of 1973 (ESA) provides Federal protection for threatened and endangered species. Fundamental to ESA protection is ensuring that Federal activities do not jeopardize the continued existence of listed species. Federal agencies (action agencies) undertaking or permitting projects, including everything from transportation improvement to energy development to habitat restoration, consult with the US Fish and Wildlife Service (USFWS) and/or National Marine Fisheries Service as prescribed by Section Seven of ESA. A conservation benefit of consultation is the negotiation of changes to project design that lessen negative impacts. Changes may include improved best management practices, modified project timing, location, or design, or compensatory restoration actions.

The USFWS Washington Fish and Wildlife Office in Lacey, Washington (WFWO) is responsible for consultations for a number of threatened and endangered species. Notably, the federally-threatened bull trout (*Salvelinus confluentus*) was, in recent years, the subject of approximately 85% of WFWO consultations. However, the office has recently experienced reductions in staffing levels, which have led to overruns in regulatory deadlines for completing consultations. When overruns occur, opportunities to negotiate changes are lost. Therefore, managers at the WFWO wanted to develop a method to guide decision-making about staff time allocation. Here, we describe a decision-analytic framework (sensu Clemen, 1996) developed to help managers allocate staff time to the WFWO bull trout consultation workload to maximize the conservation value of consultation, while completing work within regulatory deadlines.

General aspects of this framework have wide applicability both to USFWS, and more generally to organizations interested in the optimal allocation of scarce conservation resources, especially for

conservation actions targeted at single species. Where other allocation case studies have focused on total budget constraints, here we focus on constraints imposed by limited staff time and regulatory deadlines (i.e., the legal requirement to respond to all consultations and to do so within legally-mandated timeframes). By demonstrating how the notion of constrained optimization for conservation problems extends beyond cost constraints, we provide a fuller picture of how these methods can be broadly valuable to managers interested in maximizing conservation returns.

## 2. Materials and methods

### 2.1. Bull trout ecology

The bull trout is federally threatened throughout its range in the northwestern US. Bull trout are primarily a migratory species, spawning in headwater tributaries in the fall and migrating downstream in the winter and early spring to forage, mature, and overwinter (Montana Bull Trout Scientific Group, 1998; Brenkman and Corbett, 2005). Fluvial (river migrant) and adfluvial (lake migrant) life history forms of bull trout are represented throughout the range. The Coastal and Puget Sound regions of western Washington contain the only populations supporting the anadromous (marine migrant) life history (Goetz et al., 2004; Brenkman et al., 2007) which exhibits complex migrations between freshwater and salt-water habitats during the life cycle (Brenkman et al., 2007).

Bull trout have more specific habitat requirements than most salmonids (Rieman and McIntyre, 1993). Water temperatures above 15 °C limit their distribution (Rieman and McIntyre, 1993). Bull trout are sensitive to habitat changes that decrease water quality and quantity, reduce habitat connectivity, increase stream substrate embeddedness, simplify stream channel complexity, and reduce instream habitat complexity (Montana Bull Trout Scientific Group, 1998).

We focus here on the Coastal–Puget Sound population segment, which contains 14 core areas encompassing 67 local populations (interacting spawning groups). Core areas are planning units that form the basis of the draft recovery plan (US Fish and Wildlife Service, 2004), and combine core habitat (i.e., habitat that could supply all elements for long-term viability of bull trout) and a core population (one or more local populations). Habitat management objectives within core areas include maintaining cold stream temperatures, high water quality, complex and diverse channel characteristics, and large patches of connected habitat. The anadromous form is unique in its reliance on nearshore marine and freshwater habitats outside of core areas for foraging and overwintering.

### 2.2. Decision analysis

The decision problem is how to allocate staff time to bull trout consultation. Authority for this decision lies with the WFWO management team, and in consultation with this team, we developed a statement of the management objective: Maximize the conservation effectiveness of bull trout consultation, while completing work within regulatory time frames. By regulation, the duration of consultation varies depending on the expected consequences: 30 days for projects with “insignificant or discountable” effects (informal consultation) or 135 days when “significant” effects are anticipated by the action agency or Services (formal consultation).

For alternative actions, we specified that each consultation could be assigned to either a short bin or a long bin, where the short bin consultations would be completed in a minimum amount of time without negotiating changes with the action agency. For long bin consultations, biologists would invest time negotiating changes to benefit bull trout. Scaling these alternatives up to apply

to the many consultations that arrive in the WFWO, we aimed to develop a decision rule that identified the optimal proportion of consultations to place in the short versus long bin, and for consultations in the long bin, the optimal amount of time staff biologists should invest in those consultations. The optimal decision rule could then be converted into guidance whereby consultations with a potential value score (described below) under some cutoff should optimally be placed in the short bin, and those above the cutoff in the long bin.

Our approach to identifying optimal allocation involves two steps. First, each consultation is assigned a relative score that measures the potential conservation gain associated with investing staff time to negotiate beneficial changes in the project; this is the prioritization step, which we achieve with our potential value (PV) model. Second, once the relative conservation value of investing time in individual projects is determined using the PV model, our workload allocation model predicts the optimal decision rule for the suite of projects, where alternative decision rules vary in the proportion of projects to be placed in the long versus short bins, and the amount of time to spend on projects in the long bins; this is the allocation step. We describe each of these models in detail below.

### 2.3. Working with experts

During model development, we encountered information gaps for which empirical data were unavailable. We elicited this information from a panel of five experts from the consultation staff of the WFWO and the USFWS Regional Office in Portland, Oregon. Criteria for selecting experts (e.g., Hart, 1986) emphasize specialized training, knowledge, problem solving effectiveness, and communication skills. Our criteria for experts were: extensive experience with bull trout consultation, professional recognition by peers as an expert, and ability to work in a group setting.

We elicited information from the expert panel during a 4-day workshop at the WFWO in October 2007, with preparation by the panel during the preceding month. The panel was asked to provide input needed to develop the PV model, and to provide input on how time invested in a consultation would result in increased realization of the potential value of the project (see below). Our elicitation technique was a modification of the Delphi process (e.g., Vose, 1996) and included providing experts with background materials, eliciting the conceptual model or function, portraying individual results, reviewing and revising, and aggregation of consensus results.

### 2.4. Potential value model

We developed the PV model for estimating the conservation value gained by investing staff time in negotiating changes to a pro-

ject. We assumed all projects had an inherent impact on bull trout, which could broadly be characterized as negative, neutral, or positive. The impact of a project was viewed as falling along a continuum. We defined the PV as the amount of positive movement along this continuum anticipated from a staff biologist working to negotiate changes to the project. In other words, we sought to develop a measure of the potential for improving a project to further bull trout conservation, rather than a measure of the ultimate impact of a project.

It is important to note that we built the PV model to predict potential value as assessed by our expert panel. That is, our model attempts to replicate the judgment of our experts on the potential for improving a project to further bull trout conservation, rather than to directly predict how investing time in a consultation would change biological outcomes for bull trout (e.g., as measured through demographic parameters). We assumed that the judgment of our experts corresponded well with on-the-ground realities for bull trout. Though we note that more involved monitoring to ascertain biological outcomes would be highly beneficial, linking our model to these outcomes was beyond the scope of this effort. Data directly linking consultation activities with biological responses of bull trout are not available (in fact, we know of very little data of this kind for any taxa listed under ESA). In the absence of such data, we assert that expert opinion is the best source of information for characterizing the relative value of different consultation activities, and that this opinion should prove invaluable in developing prioritization schemes for consultation workloads (see Section 4).

After an orientation meeting during which the PV concept was described, experts were provided with  $n = 50$  project descriptions for detailed review. We randomly selected descriptions from 1300 projects for which bull trout consultations had been completed during 2003–2006 (73 formal, 1289 informal). Because of the greater time required for experts to review project descriptions for formal consultations, we were able to include only 10 formal (and 40 informal) consultations. The descriptions were provided to each expert in a unique, random order. Experts were given one week, and conducted their review and scoring independently. For each project, experts provided a PV score on a scale of 0 (low) to 20 (high).

At the workshop, we worked with experts to develop a list of variables identified as important predictors of PV. We emphasized the importance of selecting variables for which values could be assessed with relatively little effort and high repeatability. A PV model that was time consuming to use would thwart our efforts to increase efficiency. The variables identified fit into two categories: variables related to the project, and variables related to the species (Table 1).

Four project variables were identified: (1) ProjTypeScale, a coarse categorization of 38 types of typical projects encountered in western Washington, incorporating a size or scale component

**Table 1**

Description of variables included in the potential value model. Variables of two types were included – those relating to the project itself, and those relating to bull trout in the area affected by the project.

Variable type	Variable name	Short description	Levels
Project	ProjTypeScale	Project type category	38 levels (e.g., large timber harvest)
	Prog	Whether project is covered under programmatic guidelines	Yes, no
	BMP	Whether best management practices have been adopted	Yes, no
	DegFlex	Degree of flexibility in design, timing, and location	Low, moderate, high
Species	LHForm	The combination of life history forms expected in the project area	Anadromous, fluvial and anadromous, adfluvial and anadromous
	LHStage	The combination of life history stages expected in the project area	Adult, egg and juvenile, juvenile and adult
	HabUnit	The habitat unit in the project area	Inside core area, freshwater outside core area, marine, other
	CoreRisk	The risk status of the core population in the project area	Low, moderate, high, outside core area
	HabCond	The condition of habitat in the project area	Pristine, degraded, highly degraded

when relevant (e.g., “small pier or dock construction” is distinguished operationally from “large pier or dock construction”); (2) Prog, describing whether a project was subject to programmatic recommendations, which are guidance provided to action agencies to streamline consultation on certain project types that are frequently submitted for consultation; (3) BMP, reflecting whether recognized best management practices were adopted in project design; and (4) DegFlex, reflecting the degree of flexibility in the project design, timing, and location.

Five species variables were identified: (1) LHForm, recording the life history form or combinations of forms expected in a project area; (2) LHStage, reflecting the life history stage or stages expected in a project area during the time of potential effects from the project; (3) HabUnit, describing the habitat unit in the project area; (4) CoreRisk, reflecting, for projects located within core areas, the risk status of the core area based on risk assessment criteria incorporating adult abundance, trend in adult abundance, and number of local populations; and (5) HabCond, assessing habitat condition in the project area.

We recognized that in some cases, when applying the PV model, levels of species variables would occur that we had not included in model fitting due to lack of data. For example, (1) fluvial, anadromous, and adfluvial life history forms do sometimes occur in the same area, or (2) if a project was large enough, it could be expected to have an impact on more than one level of the HabUnit or HabCond variables. In these cases, we apply the related coefficient resulting in the highest PV score.

Using the 50 projects and our expert’s scores, we wanted to fit a model of the form:

$$\widetilde{PV}_i = \hat{\beta}_0 + \hat{\beta}_1 * V_{1,i} + \hat{\beta}_2 * V_{2,i} + \dots + \hat{\beta}_9 * V_{9,i} \quad (1)$$

(more precisely, multiple effect estimates were associated with one variable if it was categorical). We accomplished this by fitting a linear model (Proc GLM; SAS Institute, 2003), with the mean of the experts’ PV scores for the 50 scored projects as the dependent variable, and the values of the nine variables for those projects as the independent variables.

However, because we did not have adequate data to fit the 38 identified project type and scale categories (ProjTypeScale), special treatment of this variable was required before linear model fitting. We worked with experts to associate a score for each of the 38 project type and scale categories, with category the only information provided to experts on which to base their score. We refer to these as project type and scale sub-scores. We integrated the project type and scale sub-scores into the linear model by converting the relevant sub-score for each of the 50 projects in the dataset to a standard normal scale. The normalized sub-score for project  $i$  ( $S_i^N$ ) was computed as:

$$S_i^N = \frac{S_i - \bar{S}}{\sqrt{\frac{\sum_{i=1}^n (S_i - \bar{S})^2}{n-1}}} \quad (2)$$

where  $S_i$  is the project type and scale sub-score for project  $i$ ,  $\bar{S}$  is the project type and scale sub-score averaged across the 50 projects, and  $n$  is the sample size (i.e., 50). We then used the normalized sub-score as the independent variable in the linear model (ProjTypeScale). We did this because in several cases the value of  $S_i$  for a project was greater than the mean PV score for the project provided by the panel; it was therefore necessary to rescale the sub-scores to integrate them into the final PV model.

While the available data for fitting the PV model were limited (50 projects), we chose to fit all nine of the variables (many of which had multiple levels) specified by the expert panel, rather than take a parsimonious model selection approach (sensu Burnham and Anderson, 2002). This was because we were

primarily interested in developing a model that could grow with the WFWO over time, where additional monitoring data could be used to improve the fit of the model in the future.

## 2.5. Handling time curves

We also needed information on the relationship between time spent on a consultation (i.e., handling time) and the proportion of PV realized. For projects in the short bin, by definition, no time would be invested by staff in negotiating changes. Therefore, the PV realized would be 0 for all short-bin projects. Logically, these consultations should be completed in as short a time as possible, to avoid wasting resources where conservation improvements are not realized. We worked with the experts to determine minimum handling times necessary to complete projects in the short bin (i.e., read the biological assessment, write the response, etc.). We elicited an estimate of minimum handling time for both informal and formal consultations from each member of the expert panel, and by consensus, used the averages across experts.

We also elicited handling time curves by first asking each expert to draw a curve relating handling time (in units of 8-h days) to the proportion of PV realized for both informal and formal consultations. In the first round of elicitation, most experts drew a logistic-type curve, and, when the experts then discussed their individual curves as a group, they decided unanimously that a logistic-type curve was most appropriate. Next, each expert drew their own logistic curves by hand for both informal and formal consultations. We selected four points on each curve (0% PV realized, 5%, 50%, and 95%), and used a numerical optimization technique (separately for the formal and informal handling time curves) to minimize the sum of squared differences between the points on the experts’ curves and a function of the general form:

$$\text{Proportion of PV realized} = \frac{e^{a+b*H}}{1 + e^{a+b*H}} \quad (3)$$

(i.e., a logit function) where  $H$  is handling time and  $a$  and  $b$  are estimated parameters. We used the “nlm” function in the R programming environment (R Development Core Team, 2004) for numerical optimization. To integrate uncertainty in the handling time curves into the decision analysis, we extracted both the mean estimates of the parameters and the estimated variance–covariance matrix from the numerical optimization procedure. We then randomly generated 50,000 pairs of these parameters which integrated the uncertainty reflected in the variance–covariance matrix, as follows:

$$\hat{\beta}_{new} = \hat{\beta}_{mean} + (V^T * R) \quad (4)$$

where  $\hat{\beta}_{new}$  are a randomly-generated pair of parameters  $a$  and  $b$ ,  $\hat{\beta}_{mean}$  are the fitted estimates of  $a$  and  $b$ ,  $V$  is the Choleski decomposition of the variance–covariance matrix,  $R$  is a vector composed of two random deviates from a standard-normal distribution, and  $T$  signifies a matrix transpose. We kept only those parameter pairs that produced handling time curves with positive slopes (i.e.,  $b > 0$ ). These were fed into the workload allocation model, which randomly chose one of these pairs of parameters for each simulation (as described below).

## 2.6. Workload allocation model

A simulation model was developed (in the R programming environment; version 2.5.1, 2007) to predict the outcome, in terms of total PV realized, of different decision rules (i.e., levels of the management control variables). Fig. 1 provides a diagrammatic representation of the inputs and outputs of the model. There were four management control variables, including the amount of



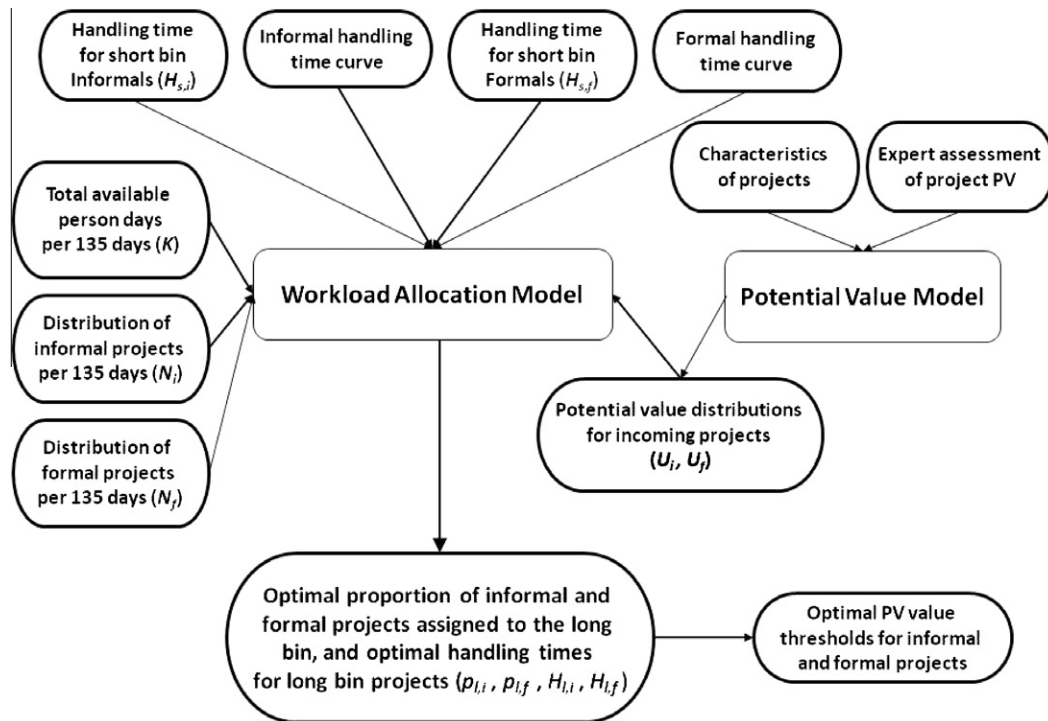


Fig. 1. Diagram of inputs to and outputs from the workload allocation model. Symbolic representations of quantities provided in parentheses reference those provided in text.

handling time to expend on (1) informal and (2) formal projects in the long bin, and the proportion of (3) informal and (4) formal projects assigned to the long bin.

The workload model simulates a consultation workload over a 135-day period (the maximum consultation time frame) under different levels of the control variables. While there are four control variables, only three are independent, and the fourth is computed by solving for it in Eq. (5), due to the constraint that the workload must be completed in the available staff time:

$$K = N_i^* p_{l,i}^* H_{l,i} + N_i^* (1 - p_{l,i})^* H_{s,i} + N_f^* p_{l,f}^* H_{l,f} + N_f^* (1 - p_{l,f})^* H_{s,f} \quad (5)$$

where  $K$  is the total available staff time;  $H_{s,i}$ ,  $H_{l,i}$ ,  $H_{s,f}$ , and  $H_{l,f}$  are handling times for short bin informal, long bin informal, short bin formal, and long bin formal consultations, respectively; and  $p_{l,i}$  and  $p_{l,f}$  are the proportion of informal and formal projects placed in the long bin. To clarify,  $H_{l,i}$ ,  $H_{l,f}$ ,  $p_{l,i}$ , and  $p_{l,f}$  are the control variables, though only three of these are independent and the last must be obtained by subtraction using Eq. (5). The variables  $N_i$  and  $N_f$  are the total number of informal and formal consultations arriving in a 135-day period. In model runs, these were sampled from distributions, which were in turn calculated from an office database that tracks project arrival. During federal fiscal years 2003–2006, 117 (SD = 59) informal consultations and seven (SD = 3) formal consultations were submitted to the WFWO, on average, during each 135-day period.

Additional inputs to the model were vectors of PV scores, calculated as the predicted values from the PV model, for a set of informal ( $U_i$ ;  $n = 50$ ) and formal ( $U_f$ ;  $n = 47$ ) projects randomly selected from the office database (including the 50 projects used to develop the PV model). These vectors estimate the distribution of PV scores for arriving projects. Finally, the handling times of projects assigned to the short bin, both informal ( $H_{s,i}$ ) and formal ( $H_{s,f}$ ) were used in the model.

The workload allocation model proceeded as follows:

1. First, particular levels of each of the three independent management control variables ( $H_{l,i}$ ,  $H_{l,f}$ ,  $p_{l,i}$ ), were selected from a specified range.
2. For each simulation at the given levels of the management variables (20–1000 simulations were run during explorations of model behavior), the numbers of informal ( $N_i$ ) and formal ( $N_f$ ) projects arriving in the WFWO over a theoretical 135-day period were sampled from normal distributions (with means and standard deviations given above; we truncated the samples to produce integers for  $N_i$  and  $N_f$ ). Also, the parameters  $a$  and  $b$  associated with the handling time curves for both informal and formal consultations were chosen at random from randomly-generated lists of pairs of these parameters (developed as described above).
3. Based on the values of the management variables ( $H_{l,i}$ ,  $H_{l,f}$ ,  $p_{l,i}$ ), as well as the number of projects in the simulation ( $N_i$  and  $N_f$ ), and  $K$  (the value of which was provided by office managers),  $p_{l,f}$  was calculated by solving Eq. (5).
4.  $N_i$  values were randomly selected from  $U_i$ , and  $N_f$  values were selected from  $U_f$ . These values (which formed the vectors  $x_i$  and  $x_f$ ) represented the PV scores for theoretical projects arriving in the WFWO over the 135-day period.
5. Informal projects for which  $x$  was greater than the  $(1 - p_{l,i})$  quantile of  $U_i$  were assigned to the long bin, as were formal projects with  $x$  greater than the  $(1 - p_{l,f})$  quantile of  $U_f$ ; all other projects were assigned to the short bin. We used the quantiles of  $U$ , rather than  $x$ , because the decision rule would have to be specified before the distribution of the potential values for any 135-day time period was known.
6. Based on this assignment, the PV realized for each project was calculated as follows:
  - a. For projects in the short bin, PV realized = 0.
  - b. For projects in the long bin, PV realized was calculated as:

$$R = x^* \frac{e^{a+b^*H}}{1 + e^{a+b^*H}} \quad (5)$$

(see Eq. (3)) where  $H = H_{i,i}$  for informal projects and  $H = H_{i,f}$  for formal projects, and where  $a$  and  $b$  were estimated as described above.

7. Handling time was calculated (equal to the sum of the number of projects in each category – short informal, long informal, short formal, and long informal – multiplied by the handling time for each category). If a relatively high proportion of the randomly-selected projects had high PV scores (i.e., large  $x$ ) it was possible to have a total handling time that exceeded  $K$ . In this case, to reflect the legal mandate to process all incoming consultations within the required timeframes, the total PV realized in the simulation was set to 0 (to penalize decision rules that regularly resulted in time overruns). Otherwise, the PV realized was calculated as the sum of PV realized across all projects.
8. Total PV realized was averaged over simulations, as was the value of  $p_{i,f}$  from Step 3.

### 2.7. Optimization

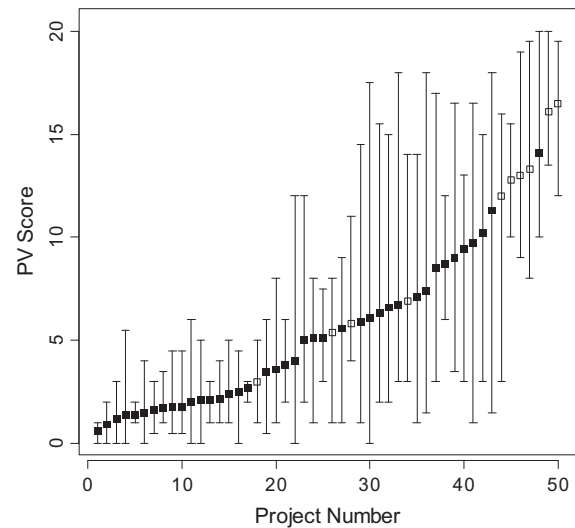
We examined simulation output to determine the values of the management variables that yielded the greatest PV realized. We simulated over progressively narrow ranges of the management variables to locate optimal (or near-optimal, given simulation error) values. We identified the values of the management variables that yielded the greatest average PV realized, as well as associated decision rules, which were specified by the values of the  $(1 - p_{i,i})$  quantile of  $U_i$ , and the  $(1 - p_{i,f})$  quantile of  $U_f$  (where  $p_{i,f}$  is the average calculated in Step 8 above). These quantile values specify the minimum PV scores required to assign informal and formal projects, respectively, to the long bin.

### 3. Results

The average PV scores and the ranges across experts for the 50 projects used to develop the PV model are presented in Fig. 2. While for some projects the range in scores across experts was large, correlations between experts were high. The correlation coefficient relating the individual scores for each expert with the average scores for the remaining experts was greater than 0.75 in all but one case (expert 1, 0.78; 2, 0.76; 3, 0.80; 4, 0.49; 5, 0.76).

Estimated regression coefficients, standard errors (SE), and coefficients of variation (CV) for the PV model are presented in Table 2. Within project variables, patterns in the coefficients were as expected. The coefficient for ProjTypeScale was positive – as the project type and scale sub-score increased, so did the PV score. Prog had a negative coefficient which appeared sensible as programmatic agreements determine management of standard types of projects so time investment in these consultations should be consequently reduced. The coefficient for the BMP variable was negative indicating that projects with best management practices already in place would receive lower priority. Finally, within the DegFlex variable, high flexibility led to higher PV scores and low flexibility to lower PV scores, reflecting the increased ability to negotiate beneficial changes with more flexible project design.

Within species variables, patterns in the coefficients were also generally as expected, although the estimates were in many cases highly uncertain. Within the LHForm variable, higher PV scores applied to projects affecting multiple life history forms, with lower scores for projects only affecting anadromous bull trout. Because the adfluvial life history form is rare within the Coastal–Puget Sound region, the positive coefficient for adfluvial and anadromous relative to fluvial and anadromous was not unexpected. Within the LHStage variable, projects affecting only adult life stages would



**Fig. 2.** Mean potential value scores (squares) provided by the five members of the expert panel, arranged from lowest to highest, for the 50 projects used to develop the PV model. Error bars show the ranges of the scores across the experts. Filled squares represent projects that were informal consultations and open squares were formal consultations.

receive lower PV scores, which is sensible as these projects are located outside the more sensitive spawning and early rearing habitats that may contain eggs or juveniles. The pattern for estimated HabUnit coefficients was not immediately intuitive. The lower coefficient estimated for inside core area as compared to freshwater outside core area and marine is counter to the life history form coefficients (i.e., only the anadromous life history form uses habitat units outside of core areas). However, there has generally been a greater focus on and more detailed understanding of freshwater habitat use by bull trout relative to marine habitat use. Therefore, projects in critical freshwater areas tend to be better designed to minimize effects on bull trout. For CoreRisk, core areas of all risk levels had positive estimated coefficients, indicating prioritization of projects in core areas. The fact that the highest coefficients were estimated for both low and high risk core areas may reflect experts' desires to protect the best core areas while also trying to improve conditions in those at greatest risk. For the HabCond variable, results indicated lower PV scores for projects in highly degraded or degraded areas. This may reflect greater emphasis on negotiating changes to reduce impacts in intact habitats, versus in reduced quality habitats.

The mean handling time curve (Eq. (3)) for informal consultations is presented in Fig. 3 (red line;  $a = -3.33$ ,  $b = 0.55$ ), along with 50 randomly generated curves reflecting uncertainty in the parameters.<sup>1</sup> For formal consultations this information is shown in Fig. 4 ( $a = -4.00$ ,  $b = 0.12$ ). The handling time curve for informal consultations is much steeper than for formal consultations. In the informal consultation handling time curve, 95% of the PV is realized by ~11 days, versus in the formal consultation handling time curve ~58 days. Minimum handling times, which were elicited from the experts for informal and formal consultations, were 1.5 and 14.2 days, respectively (the handling time curves are truncated below the minimum handling times).

Results from the workload allocation model simulations indicated that the greatest total PV realized would occur with handling times  $H_{i,i} = 7$  days (informal projects), and  $H_{i,f} = 15$  days (formal projects), and with the proportion of informal projects in the long bin ( $p_{i,i} = 20\%$ ) (Fig. 5). From Eq. (5), we get  $p_{i,f} \approx 0.82$ . These

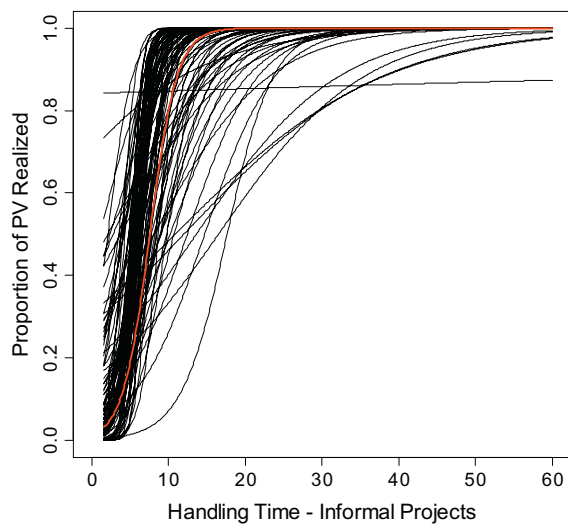
<sup>1</sup> For interpretation of color in Figs. 3–5, the reader is referred to the web version of this article.

**Table 2**

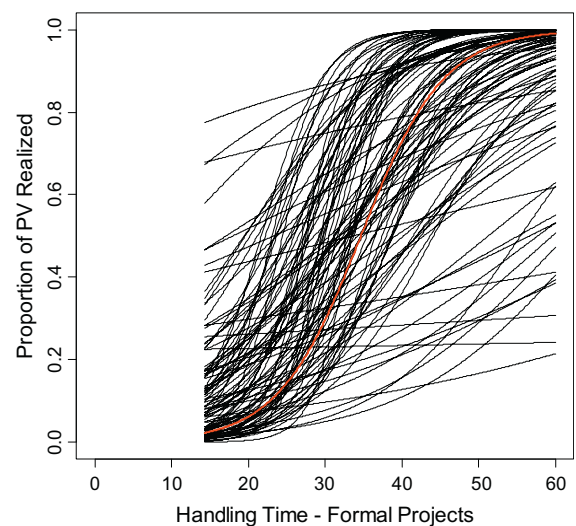
Linear model for potential value, developed by scoring projects submitted to the Washington Fish and Wildlife Office Complex for Section Seven consultation. Results include regression coefficients, standard errors (SE), and coefficients of variation (CV). Variables of two types were included in the model – those relating to the project itself, and those relating to bull trout in the area affected by the project. Variables are defined in the text.

Variable Type	Variable	Level	Coefficient (SE)	CV (%)
Intercept	Intercept	–	11.33 (4.44)	39
Project	ProjTypeScale	–	0.89 (0.60)	67
	Prog	Y	–1.67 (1.28)	77
		N	0.00 <sup>a</sup>	
	BMP	Y	–0.48 (1.21)	251
		N	0.00 <sup>a</sup>	
	DegFlex	Low	–1.92 (1.17)	61
		Moderate	0.00 <sup>a</sup>	
		High	2.85 (2.52)	88
Species	LHForm	Anadromous	–0.38 (3.36)	877
		Fluvial and anadromous	0.00 <sup>a</sup>	
		Adfluvial and anadromous	1.01 (3.92)	388
	LHStage	Adult	–4.05 (1.87)	46
		Egg and juvenile	–0.34 (2.50)	724
		Juvenile and adult	0.00 <sup>a</sup>	
	HabUnit	Other	0.00 <sup>a</sup>	
		Inside core area	0.05 (3.90)	8118
		Freshwater outside core area	0.51 (1.50)	293
		Marine	3.01 (1.79)	60
	CoreRisk	Outside core area	0.00 <sup>a</sup>	
		Moderate risk core area	0.65 (5.16)	791
Low risk core area		2.66 (4.65)	175	
High risk core area		2.66 (5.26)	197	
HabCond	Highly degraded	–1.47 (1.74)	118	
	Degraded	–1.24 (1.64)	132	
	Pristine	0.00 <sup>a</sup>		

<sup>a</sup> For each of the class variables, a default category is estimated by the intercept (and has a coefficient value of 0) while the other category coefficients represent the difference between the given category and the default category, i.e., “Y” in “Prog” represents the difference between “N” and “Y”.



**Fig. 3.** For informal projects – the relationship between handling time and the proportion of a project's potential value (PV) that is realized through the consultation process (see Eq. (3) in text). For the estimated coefficients ( $a = 0.176$ ,  $b = 0.907$ ), half of the potential value is realized in 7.0 days, 95% in 10.3 days. Note that the curve is truncated below 1.5 days, which is the minimum handling time of formal projects. The red line is the curve at the values of the estimated coefficients, while the black lines are curves randomly generated given the uncertainty in the estimated coefficients; the workload allocation model uses these randomly generated curves to account for uncertainty.

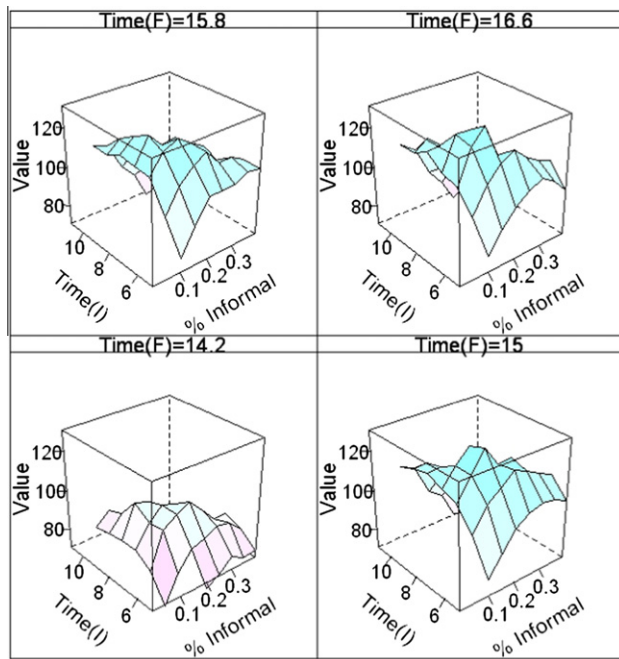


**Fig. 4.** For formal projects – the relationship between handling time and the proportion of a project's potential value (PV) that is realized through the consultation process (see Eq. (3) in text). For the estimated coefficients ( $a = 0.082$ ,  $b = 0.215$ ), half of the potential value is realized in 33.1 days, 95% in 46.9 days. Note that the curve is truncated below 14.2 days, which is the minimum handling time of formal projects. The red line is the curve at the values of the estimated coefficients, while the black lines are curves randomly generated given the uncertainty in the estimated coefficients; the workload allocation model uses these randomly generated curves to account for uncertainty.

proportions produce a decision rule whereby projects with PVs greater than 7.3 for informal projects and 3.2 for formal projects would be placed in the long bin.

We also explored optimization under conditions of greater staff resources; one can think of this as reframing the problem from the standpoint of the regional office, which determines the local

office's budget. We were interested in how the staff allocation and expected performance might change as a function of budget. Simulations indicated that by doubling staff time, handling time of long informal projects would increase from seven to nine days, proportion of informal projects in the long bin would increase from 20% to 40%, handling time of long formal projects would increase



**Fig. 5.** Results of workload allocation model runs with variable levels of handling time for formal consultations (panels), handling time for informal consultations (y-axis), and proportion of informal consultations in the long bin (x-axis). The z-axis gives the total potential value realized, and indicates that the optimal decision rule involves 15 days handling time for formal consultations (lower right panel), 7 days handling time for informal consultations, and 20% of informal consultations in the long bin.

from 15 to 26.2 days, and proportion of formal projects in the long bin would increase from ~82% to ~93%; the cumulative result of these changes would be more than a doubling of total PV realized.

#### 4. Discussion

Our work fits within a growing class of case studies, distributed worldwide, concerned with the optimal allocation of conservation resources (e.g., Moilanen and Cabeza, 2002; Marsh et al., 2007; Martin et al., 2007; McBride et al., 2007; Murdoch et al., 2007; Wilson et al., 2007; Bottrill et al., 2008; McCarthy et al., 2008). Many of these investigations have concerned themselves with the optimal allocation of resources, usually financial resources, to the conservation of multiple species. Our work can be seen as analogous, with the allocation made across different efforts to conserve one species, when the constraints are imposed by limited staff time and legally-mandated regulatory timelines for all projects. Thus, our framework shows how the application of constrained optimization methods has an even wider applicability for conservation management.

We note several useful points regarding the development of a resource allocation framework. First, it is critical to begin by developing an accurate and precise statement of objectives (Keeney, 1992; Murdoch et al., 2007). The objective will, as it should, greatly influence the optimal decision. For example, had the managers of the WFWO asked us to minimize the time spent on bull trout consultation, perhaps so they could direct those staff resources to other species, subject to some constraint on the amount of conservation achieved, our results would obviously have been very different.

Second, uncertainty need not prevent development of a decision-analytic framework (e.g., Williams, 1997; Moilanen et al., 2006; McBride et al., 2007). We faced serious uncertainty about

the effects of federal projects on bull trout and the potential for consultation to affect the conservation outcome. However, we worked with experts to develop the PV model and we integrated uncertainty in the handling time curves into our analysis; further monitoring will refine these components over time. Uncertainty should not be an impediment to decision analysis of conservation problems; rather, it should be a central feature.

Third, prioritization is not, in itself, a complete decision analysis (Wilson et al., 2006; Murdoch et al., 2007). The follow-up step to prioritization is allocation of resources to the prioritized list. Further, the prioritization and allocation steps cannot be fully decoupled, as each has consequences for the other. Thus, a full decision analysis of problems of this sort involves integrated analysis of the prioritization and allocation steps.

Fourth, proper decision framing is critical. As the budget-doubling scenario (Section 3) demonstrates, a problem that can be viewed as a constrained optimization at the level of the local manager might also be viewed as an optimal budgeting question at a higher level in the organization. That is, the staff time or office budget is a constraint from the standpoint of the local manager, but it is actually the decision variable from the standpoint of the regional office, which sets the local office's budget. Often, the creative initiative that turns the question of "what can we achieve with this budget?" into "how much more could we achieve with a bigger budget?" opens up a profoundly different approach to the problem at hand.

#### 4.1. Value of decision-analytic process

More specifically, several insights emerged during framing this decision problem which had not previously been obvious to the WFWO staff. One primary insight was that the average time spent on a consultation is strongly limited by available staff time. This constraint (Eq. (5)) places bounds on handling times and the proportion of projects in the long bin. While intuitive, formal realization of this fact allowed managers to refocus their attention from biological prioritization to workload allocation.

A second insight involved the role of the expected arrival rates of consultations. Tension arises because the number of consultations exceeds staff capacity, at least if everything is put into the long bin. With fixed staff capacity, the solution to an increasing workload is to put more projects in the short bin, and thus reduce realized PV. Therefore, the expected number of consultations per time period strongly determines the optimal strategy. This suggests an approach: reduce the incoming consultation rate, perhaps as the USFWS Midwest Region has done (<http://www.fws.gov/midwest/endangered/section7/s7process/index.html>). Again, this underscores the point that the act of framing a decision, and undertaking preliminary analysis, can often give rise to new creative alternatives.

A third insight came through development of the handling time curves, which indicated that there were, past some point, diminishing returns to be gained from continued investment in consultation. While also intuitive, this was not formally recognized in the historical approach to workload allocation, where biologists would devote time to consultations with a view toward improving each project as much as possible. Without the overrun problem, this was an appropriate (and admirable) approach to consultation, but when the workload exceeded staff capacity, this approach exacerbated time overruns.

The shape of the handling time curves led directly to the result that was most surprising: relatively little time should be devoted to formal consultation. The optimal handling time identified for informal projects in the long bin was seven days; on the handling time curve this translates to ~62% PV realized (Fig. 3). For formal projects, the optimal handling time in the long bin was 15 days, with ~10% PV realized (Fig. 4). While optimally 82% of formal

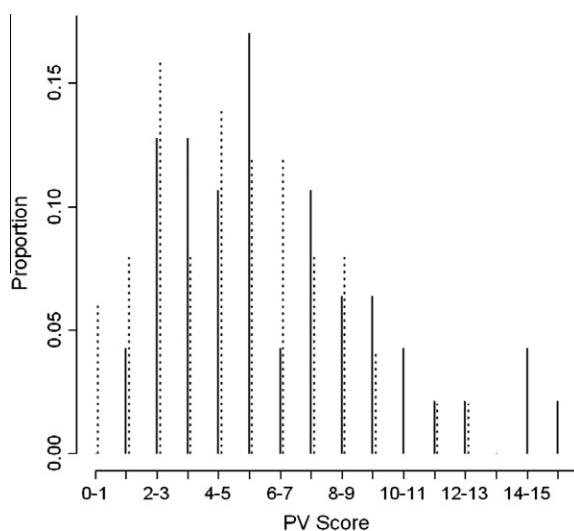


projects should be placed in the long bin (versus only 20% of informal projects) the handling time of those projects is only marginally greater than the handling time in the short bin (i.e., 14.2 days). But despite the higher handling time required to realize a similar proportion of PV, projects resulting in formal consultations do not appear to have substantially higher PV scores, based on the PV model. For the 97 randomly-selected projects used to estimate the PV score distributions for informal ( $U_i$ ;  $n = 50$ ) and formal ( $U_f$ ;  $n = 47$ ) consultations used in the Workload Allocation Model, the distributions were similar (Fig. 6) with average PV score for formal consultations = 6.4 (range = 1.0–15.5) and for informal consultations = 5.1 (range = 0.52–12.3). The result is that, given the longer handling time to exact similar benefits, the optimal solution is to expend less effort on formal consultations. Under the optimal decision, staff would devote about 304 staff days during each 135-day period to informal consultations (117 projects \* (20% \* 7 days + 80% \* 1.5 days)) and only 104 staff days to formal consultations. These specific results depend, of course, on the particular parameters of this case study, for instance the expected arrival rate of consultations, the expected distribution of PV scores, etc. Understanding these links can provide insight into innovative ways to approach the problem.

#### 4.2. Application of the decision framework

This decision-analytic framework has been adopted by the WFWO, where the PV model and optimal decision rule help determine the importance of working on a particular consultation and how to allocate staff time to consultations. This work has also influenced consultation in more subtle ways. For example, there is a new emphasis on developing strategies to allow biologists to complete short bin consultations as quickly as possible.

We note that, while we did not build a decision framework that is explicitly state-dependent, i.e., where decisions about how much time to spend on a given consultation are made based on the number of projects in the office at any given time, as might be suggested by queueing theory (Gross and Harris, 1998), tactical decision-making can integrate state-dependent thinking. For example, if the number of projects arriving in the office at a particular time is low, managers may ask biologists to spend more time on consultations with particularly high PV. If applied judiciously,



**Fig. 6.** The distribution of potential value scores amongst 97 projects potentially affecting federally-threatened bull trout, submitted to the WFWO for Section Seven consultation. Scores were generated with the potential value model for 47 formal consultations (solid lines) and 50 informal consultations (dashed lines).

such adjustments could serve to increase the overall conservation value of the consultation process.

Managers are using greater care when applying the decision rule to formal than to informal consultations because of a concern that the optimal handling time for long bin formal consultations may not be adequate. This may be the result of a deficiency in the PV model (which does not predict substantially greater scores for formal consultations) or it may suggest that additional considerations are paramount when dealing with higher-profile formal consultations.

In addition, under ESA, if the USFWS determines that a Federal action results in “Jeopardy” to the species, the action cannot go forward as proposed. Jeopardy findings only occur in formal consultations, and given that each consultation will be read by a qualified biologist, and especially given the extra care put toward formal consultations in the application of this decision tool, we are confident that this does not compromise the WFWO’s ability to identify and appropriately prioritize consultations that may result in Jeopardy.

In considering application of this tool, it is important to recognize that management recommendations cannot always be carried out as intended because of inadequate technical knowledge, physical constraints, or sociological or psychological constraints, that is, managed systems are only partially controllable (Williams, 1997). One particularly challenging aspect of partial control here concerns the strong conservation ethic of the consultation staff, which emphasizes improving each individual project as much as possible. It is difficult to change this ethic based on the advice of a decision-analytic model. Development and discussion of this framework has begun to reshape the approach to consultation, but a new approach to time allocation will require an adjustment by staff.

#### 4.3. Uncertainty and monitoring

An important component of decision-analytic approaches is recognition and treatment of uncertainty. Several types of uncertainty are relevant to this modeling framework, including both aleatory (process variability) and epistemic (incomplete knowledge; Regan et al., 2002). Aleatory uncertainty is represented in the model through the stochastic nature of the number of projects arriving in the office during a simulation period, as well as the particular PV values associated with those projects. Epistemic uncertainty is captured formally in the handling time curves.

Epistemic uncertainty in the PV model, however, is not captured formally. Here we chose to use only the point estimates from the PV model in predicting PV. We made this decision for several reasons which can be discussed in light of the two uses we make of the PV model. First, we built the PV model to facilitate assignment of projects to either the short or long bin, once the optimal decision rule was determined. For this purpose, assignment to a particular bin would not be facilitated by including uncertainty in the PV score. Second, we built the PV model to help us determine the optimal decision rule; expected PV scores were randomly generated for each project simulated under the Workload Allocation model and these were used to help determine optimal cutoffs for assigning projects to the short versus long bin. However, we expect that integrating sampling uncertainty into these measures of PV would have little impact on the outcome of the workload allocation model, because the cutoffs are derived by looking at a large number of simulations, and the expected PV values should end up determining the outcomes. That is, we could have, in our simulations, determined the PV score for each project sampled from the vectors  $U_i$  and  $U_f$  as not just the expected score, but from a distribution integrating the sampling uncertainty around that score. However, over many simulations, the mean results would tend to converge to the expected score, and our optimal decision rule would not vary from

what we determined (we confirmed this result with a small set of simulations). In fact, sampling uncertainty in this case seems much less important than systematic bias; that is, if we are systematically under- or over-estimating PV for particular projects, this could result in non-optimal workload allocation. However, without further data we cannot determine whether there is important systematic bias in the PV model. This illustrates the importance of monitoring for improvement of the PV model over time.

In our recommended monitoring plan, data collected for refining the PV model include PV scores based on more detailed reviews, where a team of biologists will review consultations under guidance similar to that given to the expert panel. The score provided by the reviews can be compared to the PV score estimated by the PV model to assess the accuracy of the model, and used in statistical refinement of the PV model. Monitoring data for further refining handling time curves would be provided by biologists assigned to consult on the projects, where, using an anonymous reporting system, time spent on consultations and the biologist's assessment of the proportion of PV realized will be collected, after guided discussions with these biologists on the concepts of PV and proportion of PV realized.

Finally, it is important to emphasize that, through development of the PV model, we did not link a prediction of the importance of time investment on a particular consultation back to on-the-ground realities of bull trout population status. Rather, we developed a model that would predict the experts' assessments of project importance. We assume that the experts' assessments correlate well with these realities, though this suggests the need for larger-scale monitoring of the effects of ESA-related activities on biological outcomes. We note, however, that monitoring to directly evaluate the efficacy of the consultation process appears to be an unfortunately rare component of ESA implementation (see also Campbell et al., 2002).

There are two approaches we could take to coping with the uncertainty about the correlation between the PV scores and on-the-ground realities of bull trout status: a robust approach, and an adaptive approach. The idea of a robust approach would be to identify decisions that are most robust to failure of the assumption of a strong correlation between the PV model and biological outcomes, for instance, by using info-gap theory (Ben-Haim, 2001). This approach would be called for especially if it was extremely difficult to acquire information about the relationship between PV scores and biological outcomes; the approach instead seeks decisions that perform well in the face of this uncertainty.

Under an adaptive approach, monitoring would be used to assess and improve the accuracy of the PV model as measured against biological outcomes and adapt future time-allocation decisions based on this new knowledge. To do this, predicted PV values and observed biological outcomes for projects would have to be monitored and compared. The ultimate biological outcomes of interest may be expected abundance and growth of the Coastal-Puget Sound population segment (population recovery criteria; US Fish and Wildlife Service, 2004) but more proximate metrics, like habitat quality, quantity, or connectivity might suffice. An adaptive approach could even be actively adaptive, using some experimental design to accelerate learning about this uncertainty. The ideal design, for instance, might pair similar consultations and analyze the biological impact of differential investments of time. We have not yet explored the details of either a robust or an adaptive approach, leaving those considerations to future work.

#### 4.4. Conclusions

This decision framework formalizes a shared understanding of the impact of staff availability on the effectiveness of ESA regulation. It can be seen explicitly that, as staff size declines, time

allocated to consultations must be reduced to avoid regulatory time overruns. Conversely, it can be seen that, with additional funding, a greater proportion of projects could be placed in the long bin, and more resources could be brought to bear on improving the conservation outlook for this species. However, given current resource availability, by following this framework the WFWO can increase the effectiveness of the consultation process and its contribution to the recovery of bull trout.

Limited resources are a ubiquitous condition in conservation management, necessitating smart strategies for allocating these resources. A wide variety of problem framing, modeling, and optimization approaches have been described in the literature for addressing resource allocation problems, which most typically appear as budget allocation problems. These approaches ultimately all arise from recognition of the concepts of decision analysis (Clemen, 1996; Possingham et al., 2001) which aims to increase decision-making effectiveness through deconstruction, analysis, and synthesis of the components of a decision. The framework we have described expands this literature with a problem focused on allocating limited staff resources in a situation where regulatory deadlines also constrain the allocation. Our experience suggests that this type of problem is common in conservation management, and that the framework described can provide useful insights for framing similar problems in conservation resource allocation worldwide.

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