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Research article

Quantifying expert opinion with discrete choice models: Invasive elodea's influence on Alaska salmonids

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ABSTRACT

Scientific evidence should inform environmental policy, but rapid environmental change brings high ecological uncertainty and associated barriers to the science-management dialogue. Biological invasions of aquatic plants are a worldwide problem with uncertain ecological and economic consequences. We demonstrate that the discrete choice method (DCM) can serve as a structured expert elicitation alternative to quantify expert opinion across a range of possible but uncertain environmental outcomes. DCM is widely applied in the social sciences to better understand and predict human preferences and trade-offs. Here we apply it to Alaska's first submersed invasive aquatic freshwater plant, *Elodea spp.* (elodea), and its unknown effects on salmonids. While little is known about interactions between elodea and salmonids, ecological research suggests that aquatic plant invasions can have positive and negative, as well as direct and indirect, effects on fish. We use DCM to design hypothetical salmonid habitat scenarios describing elodea's possible effect on critical environmental conditions for salmonids: prey abundance, dissolved oxygen, and vegetation cover. We then observe how experts choose between scenarios that they believe could support persistent salmonid populations in elodea-invaded salmonid habitat. We quantify the relative importance of habitat characteristics that influence expert choice and investigate how experts trade off between habitat characteristics. We take advantage of Bayesian techniques to estimate discrete choice models for individual experts and to simulate expert opinion for specific environmental management situations. We discuss possible applications and advantages of the DCM approach for expert elicitation in the ecological context. We end with methodological questions for future research.

1. Introduction

Resource managers often face decisions requiring quick action to avoid damage to ecosystems and economies but lack quantitative information to support decisions (Maguire, 2004). Managing invasive species is one example where rapid response can minimize long-term costs, but where persuasive empirical evidence for status, trends, and potential outcomes is often limited (Panetta and Gooden, 2017). Decision making with regards to biological invasions to aquatic ecosystems is inherently complex and characterized by high uncertainty. Aquatic invasions can be associated with regime shifts that can lead to widespread environmental damage and economic harm (Havel et al., 2015). The management of aquatic invasive species has also been termed a *wicked problem*, referring to the high complexity of a system in which cause-and-effect relationships between multiple components are not well understood (Evans et al., 2008; Seastedt, 2015). Decision makers can benefit from a synthesis of broader knowledge when weighing uncertainty and complexity (Vanderhoeven et al., 2017).

The past three decades have seen wide application of sorting expert opinion through elicitation and quantitative synthesis of knowledge in ecological management and the conservation sciences (Drescher et al., 2013). Expert input is used to define management problems, develop and parameterize models, and inform structured decision-making (Krueger et al., 2012). Experts are asked to convey their knowledge directly and quantitatively or indirectly by answering questions related to their experiences. Several elicitation tools are available for the direct encoding of probabilities including the Classical Approach (Cooke et al., 1988), the Sheffield Elicitation Framework (SHELF) (O'Hagan and Oakley, 2008), and the IDEA protocol (Hemming et al., 2018), to name a few. Elicitation processes involve multiple experts, where information is

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either collected independently and then combined (Cooke, 1991) or elicited through group deliberation where the Delphi method is commonly used (MacMillan and Marshall, 2005).

In the invasive species context, expert opinion is also used to inform risk screening tools, also known as weed risk assessments (Benke et al., 2011; Drolet et al., 2016). In such cases, experts provide numeric scores and supporting documentation for different risk categories, including qualitative ratings for establishment, ecological impact, dispersal ability, and management options (Carlson et al., 2008; Warner et al., 2003). After peer review, the ranking system calculates a score, where higher scores indicate higher risk compared with other listed species. While such scoring systems inform resource managers about relative risks, they fail to inform decision makers about acting. Furthermore, the quality of the expert assessment can be problematic with small groups of experts.

In the social sciences, the validity of direct elicitation of quantities has long been debated. Opponents believe that knowledge about a subject area does not readily translate to an ability to convey knowledge in quantitative terms, particularly for highly uncertain events. Experts often express their knowledge in words rather than numbers, and their attempts to assign numerical values result in heuristics and biases (Saaty, 1990; Tversky and Kahneman, 1974). For example, in rank order exercises, as the number of tasks increases, respondents apply simplification and elimination strategies that lead to bias and validity concerns (Louviere, 1988). Despite improvements through the Analytic Hierarchy Process (AHP) or Maximum Difference Scaling (MaxDiff), some theoretical issues remain—such as rank reversal and limitations on the number of rank items (Ishizaka and Labib, 2009; Louviere et al., 2015; Saaty, 1990).

1.1. Ecological context

We present a case study of Alaska's first known invasive submersed aquatic plant, *Elodea spp.* (elodea) and its invasion of salmonid freshwater habitat. The consequences of elodea invasion is considered an unknown threat to Alaska's rich commercial, sport, and subsistence salmon fisheries (Carey et al., 2016). Little is known about interactions of elodea with salmonids, except for one study finding that elodea encroaches on Chinook Salmon mating sites in California (Merz et al., 2008). Nothing is known about the species-specific relationship between elodea and salmonids.

Ecological research suggests that aquatic plant invasions are highly complex, often leading to alternate stable states (Strange et al., 2019). While the ecological role of aquatic plants remains the same regardless of whether they are invasive or native, their effects on fish and macroinvertebrates differ (Schultz and Dibble, 2012). In general, native aquatic plants have positive effects on fish and macroinvertebrate communities but invasive aquatic plants can cause negative effects on fish and other parts of ecological communities (Schultz and Dibble, 2012). Increased growth rates, defensive (allelopathic) chemical production, and adaptability to different environments (phenotypic plasticity) are invasive plant traits that can cause negative effects for fish and macroinvertebrates, with all three traits characteristic of elodea (Erhard et al., 2007; Schultz and Dibble, 2012).

Biological invasions such as elodea have the potential for both positive and negative effects on a commercially valuable salmonid population resulting in extreme uncertainty. Informing decision makers in this uncertain environment requires elicitation approaches that can track experts' trade-offs between favorable and less favorable habitat characteristics. In other words, the elicitation tool needs to match the complexity of potential environmental outcomes.

1.2. Discrete choice

We use the discrete choice method (DCM) to collect and then indirectly quantify expert opinion from a broad pool of experts (McFadden, 1973).[1] With DCM, experts focus on a suite of ecological relationships that may entail trade-offs between attribute levels that are more or less favorable to the desired outcome—a persisting salmonid population. For example, aquatic vegetation can provide additional cover for juvenile fish and enhance abundance of prey (Schultz and Dibble, 2012), but also provide preferred habitat for ambush predators such as Northern Pike (*Esox lucius*) that require aquatic vegetation for hunting and spawning (Casselman and Lewis, 1996).

DCM has been applied in environmental valuation (Carson and Czajkowski, 2014), health care (Reed et al., 2013), marketing (Borghi, 2009), and transportation (Hensher et al., 2005). Similar multi-attribute approaches have been used in the ecological domain to measure the relative importance of attributes in risk management (Cooke and Goossens, 2004) or to obtain relative risk rankings (Oppenheimer et al., 2016; Smith et al., 2015; Teck et al., 2010). However, these applications stopped short of collecting and analyzing discrete choice data to better understand, model, and then predict expert opinion to inform novel environmental situations.

We synthesize expert opinion conditional on environmental attributes with varying trade-offs for persistent salmonid populations affected by the invasion of elodea, an aquatic plant with uncertain positive and negative effects on fish. We define a persistent salmonid population as one that continues to exist or endures over a prolonged period of at least 20 years and with a net reproductive rate greater than one (Paterson et al., 2010).[2] Specifically, we use DCM to design hypothetical *salmonid habitat scenarios* describing elodea's possible effects using habitat *attributes* including prey abundance, dissolved oxygen (DO), and vegetation cover. The hypothetical scenarios are described by varying *attribute levels* ranging over specified values selected from values found in the literature and set in the experimental design.

We observe how experts choose between scenarios that they believe support persistent salmonid populations in elodea-invaded salmonid habitat. We quantify the relative importance of habitat characteristics that influence experts' choices and investigate how experts' trade off between habitat attributes (habitat characteristics). We take advantage of Bayesian techniques to estimate a random utility model providing individual-specific coefficients (part-worths). We then aggregate expert opinion over segments of the expert pool to evaluate expert agreement and performance. Finally, we simulate expert opinion for specific environmental management situations to inform decision making and investigate the sensitivity of experts' choices conditional on habitat attribute levels. We focus the elicitation on five salmonids—Sockeye (*Oncorhynchus nerka*), Coho (*O. kisutch*), Chinook (*O. tshawytscha*), Dolly Varden (*Salvelinus mulmu*), and Humpback Whitefish (*Coregonus pidschian*).

2. Methods

Description of methods is central to this paper and therefore lengthy. We first report the process of identifying an expert pool and the basic study design. We then present the choice model followed by model estimation and subsequent calculation of utility-derived importance scores. This step identifies the relative importance of habitat attributes for invaded salmonid habitat that experts believe would support persistent salmonid populations. Next, we synthesize expert opinion by calculating the probability of an expert choosing a habitat scenario with

[1] DCM is also known in economics as discrete (or stated) choice experiment and in market research as conjoint analysis (Louviere et al., 2010).

[2] We also refer to these populations as viable populations that are capable to persist.

an elodea-invasion present. Our sensitivity analysis tests the responsiveness of the predicted choice probabilities to changes in habitat attribute levels, illuminating the trade-offs that experts were willing to make.

The methods section closes with a coherence check segmenting the choice data into expert groups based on answers to a risk rating exercise. The rating task asked experts about their believed overall effect of elodea on salmonids in Alaska. For ease of design and analysis, we used Sawtooth Software package's design, data collection, and analysis (Otter, 2007; Sawtooth, 2016a, 2016b, 2014). This aspect may lower the barrier for ecologists to learn and apply DCM as a complementary method to other approaches of expert elicitation. Expert input was collected between March and April of 2015 after mailing letters of invitation and following up through phone calls.

2.1. Literature review and expert pool

We conducted an extensive literature review of 296 peer-reviewed articles to refine the elicitation problem as: "*What habitat characteristics most likely result in a viable salmonid population as elodea invades salmonid habitat in Alaska?*" The literature review also provided the sources for a four-page background document that was available to experts on all pages of the elicitation (Supplementary File 1). This summary described the latest scientific knowledge on habitat and environmental changes associated with elodea's presence in similar ecosystems. It also pointed towards possible multi-directional effects of aquatic invasive plants on fish and macroinvertebrates. The background document was intended to reduce ambiguity and maximize interpretation, usefulness and accuracy of the elicitation (Ayyub, 2001; Kynn, 2008).

We additionally used the literature review and examination of at least 50 peer-reviewed literature citations in Google Scholar to identify 111 experts who we contacted for the elicitation. We identified experts as those who have substantive knowledge of Pacific salmonids in freshwater habitat, the ecological role of submersed aquatic vegetation, or invasive freshwater aquatic plants. Recognizing the localized context of elodea in Alaska and the potential that experts may not be recognized through formal literature, we expanded the pool of potential experts to include state and federal resource managers with job titles that included fishery biologist, fisheries scientist, fish habitat biologist, and invasive species specialist (Table 1). The inclusion of these individuals brought knowledge of localized variability and local observations to the expert pool. Concentrated local knowledge and oversampling of salmonid expertise can be viewed as desirable rather than a source of selection bias (Drescher et al., 2013). The inclusion of non-local experts was aimed at minimizing the motivational bias that can occur when experts have personal stakes in the ecological issue (Sperber et al., 2013). Four experts served as key informants contributing to and testing the design of the elicitation survey.

2.2. Study design

We followed Hensher et al. (2005) in using a multi-step design process to generate the DCM. We returned to previous steps for modification as necessary. A pre-test with 20 arbitrarily selected experts yielded 12 trial responses. We used these to eliminate ambiguities from the questionnaire. We used a comprehensive literature review and help from two experts to select habitat attributes (also known in DCM as factors) and to determine attribute levels (also known in DCM as treatments). Below, we first describe important design criteria followed by attribute selection, and creation of the final choice sets for parameterizing the DCM. We conclude the study design with a brief description of the risk rating task, separate from the DCM, used as part of a coherence check.

Table 1
Distribution of expertise comparing the initial expert pool with respondents.

Expertise	Initial pool	% of total	Respondent count	% of total
Salmonids	82	74%	45	80%
Aquatic vegetation	38	34%	18	32%
Salmonids and other fishes	9	8%	7	13%
Invasive species	24	21%	12	21%
Alaska-based	80	72%	46	82%
Total	111		56	

2.2.1. Design criteria

Three critical design criteria are important to invasive species assessment. First, we distinguished salmonid habitat scenarios with an elodea invasion from scenarios showing no invasion. We then constrained habitat attribute levels to reflect ecologically relevant conditions specific to invaded and uninvaded habitat (Table 2). This design is also known as an alternative-specific design (Hensher et al., 2005). Second, we use unambiguous *a-priori* preference order in the attribute levels, setting levels to be consistent with ecological expectations. For example, more dissolved oxygen (DO), more prey, and less predation is more supportive of a persistent salmonid population. As a result, the order and sign of the estimated coefficients remains consistent with ecological expectations. Known as cardinal utility, this framework is commonly applied to decision-making under uncertainty (von Neumann et al., 1947).

The third important design criterium was selection of habitat attribute levels covering extreme values that are potentially outside the range experts are familiar with. Yet, attribute levels remain within observations found in the literature. The use of extreme values is also known as endpoint design (Hensher et al., 2005). It is more likely to cover the actual values of changing environmental attributes, an important aspect given the high uncertainty related to invasive species problems. The resulting design is smaller and more efficient and thus requires smaller samples for estimation especially when using hierarchical Bayesian (HB) approaches (Gelman et al., 2013).,[3,4] We realize

Table 2
Habitat attributes and attribute levels used in the study.

Attribute	Uninvaded habitat		Elodea-invaded habitat	
	Level 1	Level 2	Level 1	Level 2
Vegetation type and cover (%)[c]	Indigenous 0%	Indigenous 50%	Elodea 50%	Elodea 100%
Dissolved oxygen (mg/l)[a,c]	5.5	10.5	0.5	10.5
Prey abundance (mg/m^2)[a,c,d]	400	600	30	3000
Piscivorous fish (#/acre)[a,c]	5	20	20	35
Location of aquatic vegetation[b]	backwater, lake, entire habitat range			
Salmonid species[b]	Sockeye, Coho, Chinook, Dolly Varden, Humpback Whitefish			

[a] Attributes that have unambiguous a-priori preference order.
[b] Non-scenario-specific attributes.
[c] Salmonid habitat scenario-specific attributes dependent on the State of habitat variable (uninvaded or invaded).
[d] For sockeye mg/m^2 zooplankton, for all other salmonids macroinvertebrate abundance/m.^{2}.

[3] The assumed linearity between part-worth utilities (coefficients) associated with the endpoints is sufficient if the primary goal is the estimation of expert choice probabilities (Louviere et al., 2000).

[4] Following common choice design, we also designed for maximum variation in attribute levels within choice sets, equal representation of attribute levels, and approximately equal probability across salmon habitat scenarios presented in a choice set (Johnson et al., 2003).

that environmental management professionals may have significant interest in less extreme outcomes, thus we ensured experts could provide additional feedback through open comment at the end of the questionnaire.

2.2.2. Habitat attributes and levels

We incorporated a broad range of habitat attributes that key informants identified as most important to the persistence of salmonid populations in invaded freshwater habitat. Given the relative lack of research examining the effects of aquatic invasive species on salmonid habitat, we used both local and non-local sources of literature for setting attribute levels. The final set of attributes included type of aquatic vegetation, percent cover of aquatic vegetation, dissolved oxygen (DO), prey abundance, and predator density (Table 2).

The mean native aquatic vegetation cover observed in Alaska is approximately around 27% in lakes that have not been invaded and can reach 100% in elodea-invaded water bodies (Lane, 2014; Rinella et al., 2008). Considering the much lower vegetation cover of uninvaded lakes in Alaska, we set the attribute levels for vegetation cover in uninvaded waterbodies at 0% and 50%, recognizing the lack of vegetation in many of Alaska's salmonid ecosystems (Rinella et al., 2008). Consistent with rapid and extensive growth found with elodea-invasions in Alaska, we set the attribute levels for vegetation cover in elodea-invaded salmonid habitat to 50% and 100% (Lane, 2014) (Table 2).

Elodea can increase dissolved oxygen (DO) in upper waters near plants to 9 mg/l, but DO concentrations within 5 cm of the bottom substrate can reach as low as 0.4 mg/l (Spicer and Catling, 1988). Additionally, elodea die-back events can lead to perturbation of the entire lake ecosystem with very low DO concentrations (Barko and James, 1998; Burks et al., 2001; Diehl et al., 1998; Jeppesen et al., 1998). The mean DO concentration in 50 uninvaded lakes in the Cook Inlet region is 7 mg/l and lakes can reach natural levels of 11 mg/l (minimum: 5 mg/l) (Rinella et al., 2008). Consequently, we set DO levels for uninvaded habitat to a higher but narrower range (5.5 and 10.5 mg/l) and DO levels for invaded habitat to cover the larger range consistent with the literature setting levels at 0.5 and 10.5 mg/l (Table 2).

Invasive aquatic plants can also indirectly affect fish through changes in the food web, but the effects are complex and uncertain (Schultz and Dibble, 2012). Research related to ecosystem effects of aquatic invasive plants have shown both positive and negative effects on macroinvertebrates that are an important prey resource for salmonids (Erhard et al., 2007; Schultz and Dibble, 2012). In addition, we accounted for differences in prey resources. While Sockeye Salmon prey on zooplankton, other salmonids prey on macroinvertebrates.

In Alaska, macroinvertebrate abundance counts in uninvaded lakes range between $374/m^2$ and $1125/m^2$. Zooplankton biomass in uninvaded Sockeye Salmon nursery lakes ranges within similar magnitudes between 22 mg/m^2 and 2223 mg/m^2 (Edmundson and Mazumder, 2001). Since the magnitudes of zooplankton and macroinvertebrates are similar despite the difference in units, we use the same numeric values for the DCM design (Table 2). We reflect the greater variation in macroinvertebrate abundance observed in invaded ecosystems (Schultz and Dibble, 2012) by setting the prey attribute levels between 30 and 3000 for the elodea-invaded and between 400 and 600 for the uninvaded scenarios (Table 2).

Lastly, elodea beds provide habitat for Northern Pike that prey on juvenile salmon. Northern Pike also have the potential to cause synergistic interactions with elodea that can lead to invasion meltdowns with accelerated impacts on native ecosystems (Casselman and Lewis, 1996; Simberloff and Holle, 1999). Northern Pike are ambush predators that use aquatic vegetation for concealment as well as spawning habitat. Northern Pike in Southcentral Alaska can reach densities of up to 36 Northern Pike per surface acre (Sepulveda et al., 2014, 2013). We chose prey levels to be lower in uninvaded salmonid habitat and higher for elodea-invaded salmonid habitat reflecting the synergistic relationship between elodea and Northern Pike abundance (Table 2).

2.2.3. Choice sets

For the DCM choice model to robustly represent experts' evaluation of ecological trade-offs, the presented choice sets must be consistent with each expert's opinion and preferences (DeShazo and Fermo, 2002; Hensher et al., 2005). We designed this DCM study to select for habitat trade-offs within each expert's opinion of salmonid persistence. We used "adaptive choice-based conjoint" (ACBC), a multi-stage elicitation concept for DCM designed by Sawtooth Software (Johnson et al., 2003). ACBC develops choice sets interactively through a set of screening and probing questions that confine the presented range of distinct scenarios closer to the respondent's preferences (Johnson et al., 2003; Orme, 2009a). This approach consequently minimized additional unexplained utility, an advantage for uncertain resource management problems such as biological invasions. Each expert received ten final scenario choice sets. A choice set is a bundle of three distinct salmonid habitat scenarios.

The ACBC elicitation process has three stages (Fig. 1). First, there is a "build-your-own" (BYO) scenario, where experts are asked to identify attributes that support a viable salmonid population in Alaska. In subsequent screener tasks (Fig. 2), attribute combinations are clustered around the BYO and experts select scenarios that represent possibilities for supporting salmonid persistence. The screener task (Fig. 2) assembles four habitat scenarios based on the BYO and information from further probing questions identifying attribute levels that are either 'unacceptable' or 'must have' (Supplementary File 2). These probing questions provide the constraints to set respondent-relevant habitat attribute levels. The probing questions repeat as outlined in Fig. 1 and specified in Supplementary File 2. The respondent then determines, for each of the four scenarios in the screener task, whether the scenario offers a possibility for a persistent salmonid population or not (Fig. 2). We set the number of screener tasks to eight, the number of unacceptable to 5, and must-have probing questions to 4 following software suggestions (Supplementary File 2) (Sawtooth, 2016b).

The final ten tailored choice sets are comprised of salmonid habitat scenarios that the expert selected as viable possibilities in the screener tasks (Figs. 2 and 3). We estimate the DCM choice model using the responses to these final ten choice sets. Fig. 3 illustrates an example final choice set with the elicitation task defined as: "*Which one habitat most likely results in a viable salmonid population using it*?" Before the elicitation task, recall that the survey defined "viable" as a persistent salmonid population for at least 20 years. Therefore, the choice response variable is the believed persistence of salmonids. We simulated the design using five robotic respondents resulting in a D-efficiency of 75% (Sawtooth, 2016b).[5]

Lastly, we paid particular attention to the visual and tabular format of the discrete choice sets to minimize filtering heuristics (Hoehn et al., 2010). For example, we presented salmonid habitat scenarios through hypothetical habitat maps, specifying stream depth and gradient, to further limit ambiguity (Supplementary File 2).

2.2.4. Risk rating task

We assessed experts' risk projections upon completion of the DCM by asking: "*Please rate the overall effect of elodea on salmonid persistence.*" Experts could respond via a five-point semantic differential scale including significantly negative, moderately negative, no effect, moderately positive and significantly positive (Smith et al., 2015). We used this question for segmenting the expert pool into expert groups to facilitate between-group comparison of DCM results. We also used it to check expert coherence explained in section 2.6 (O'Hagan et al., 2006).

[5] The user cannot change this default of five robotic respondents.

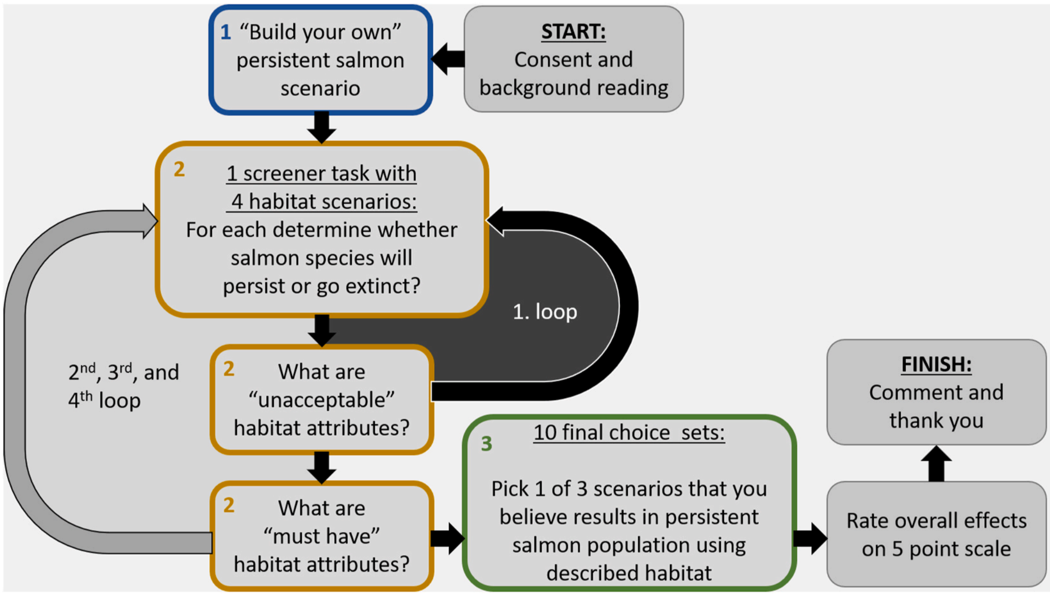


Fig. 1. The three stages of the discrete choice questionnaire using ACBC: 1) a "build your own" scenario, 2) screener tasks for preliminary salmonid habitat scenarios and important attributes, and 3) the final ten choice sets.

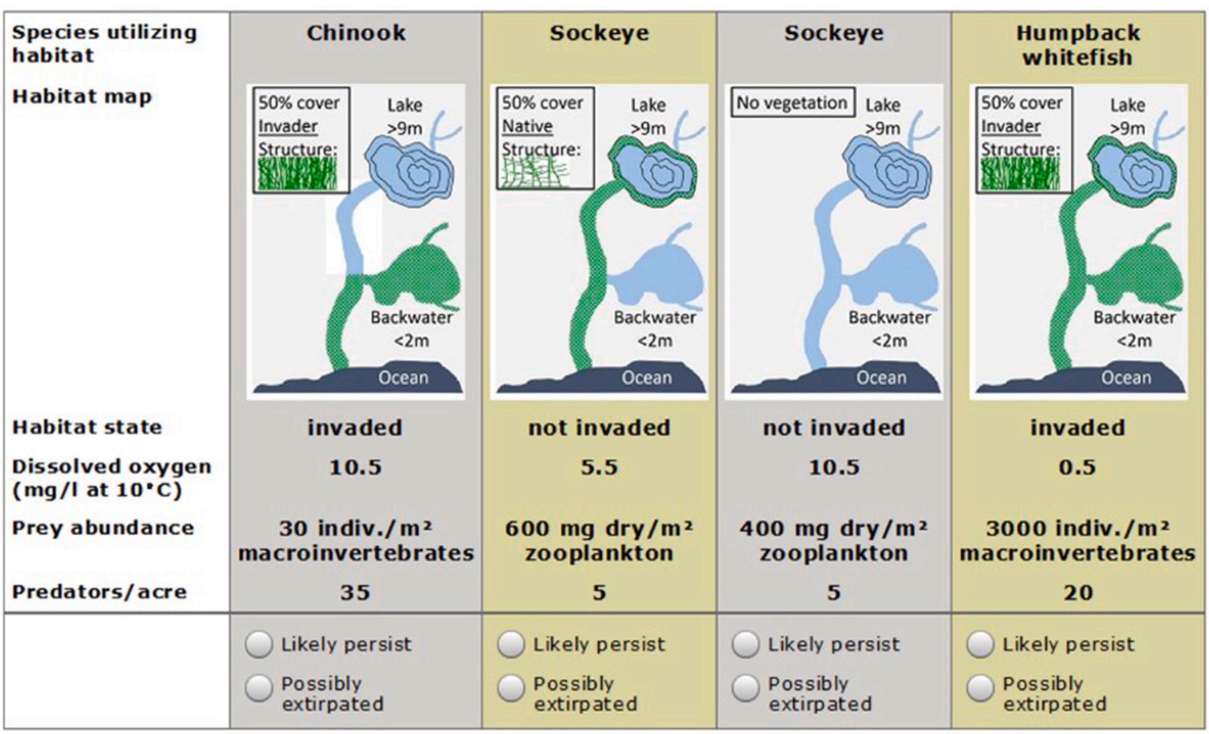


Fig. 2. Example of one of six screener tasks comprised of four scenarios each. Please note, habitat maps show aquatic vegetation cover in green, and areas of no vegetation in blue. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

2.3. Choice model

We use a random utility model to measure the influence of habitat attributes on experts' scenario choices while accounting for heterogeneity between individuals and groups of experts (McFadden, 1973). Since the DCM asks experts to select the most likely salmonid habitat scenario to result in a persistent salmonid population, the question is within each expert's professional capacity. Thus, utility represents a form of "professional utility," contrary to "individual utility." Similar arguments for this kind of theoretical support have been made by research measuring risk attitudes in professional wildfire managers (Wibbenmeyer et al., 2013). The above supports the DCM's assumption of experts making rational scenario choices.

Expert n receives utility $V_n(X_i|\beta_n)$ when scenario i occurs, where X_i is a vector of habitat attribute levels associated with scenario i and β_n is a vector of utility function parameters (part-worths) that describe expert n's preferences for scenario i over all other scenarios where $i \neq j$ and $j \in j = 1, \ldots, J$.

Experts are asked to choose among the presented scenarios for which V_n is highest. The predicted probability that an expert believes salmonid

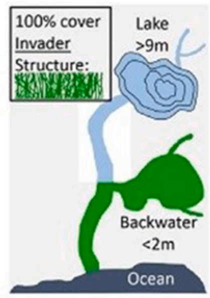
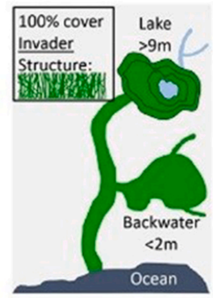
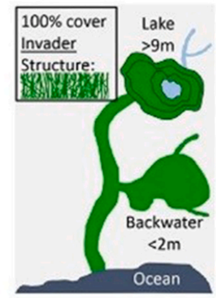
Species using habitat	Humpback Whitefish	Dolly Varden	Sockeye
Habitat map			
State of habitat	invaded by *Elodea*	invaded by *Elodea*	invaded by *Elodea*
Dissolved oxygen (mg/l at 10°C)	10.5	0.5	10.5
Prey abundance	30 indiv./m² macroinvertebrates	3000 indiv./m² macroinvertebrates	3000 mg dry/m² zooplankton
Piscivorous fish/acre	35	35	35
	○	○	○

Fig. 3. Example of one of ten choice sets each comprised of three salmonid habitat scenarios, asking experts: Which one habitat most likely results in a viable salmonid population using it?.

habitat scenario j is more supportive of salmonid persistence than salmonid habitat scenario i, is equal to the probability that the difference in unobserved utility in i compared to j, $\varepsilon_j - \varepsilon_i$, is less than or equal to the difference in observed sources of utility in j compared to i after the expert evaluates all scenarios. This statement can be expressed as follows,

$$p_i = p\left(\varepsilon_j - \varepsilon_i\right) \leq \left(V_i - V_j\right). \tag{1}$$

Equation (1) describes how experts trade off between different habitat attributes based on their preferences and professional experience. Given a multinomial logit model, the probability that expert n chooses salmonid habitat scenario i in J scenarios is as follows:

$$p_{ni} = \frac{e^{\beta_n X_{ni}}}{\sum_{j=1}^{J} e^{\beta_n X_{nj}}}, \tag{2}$$

Where p_{ni} is the probability of choosing the ith scenario,[6] β_n X_{ni} is the total utility[7] of the chosen ith scenario. We refer to p_{ni} as the *individual expert choice probability*. The sum of p_{ni} across multiple experts equals the expert group's preference for a specific salmonid habitat scenario (Lancsar and Louviere, 2008; Orme and Chrzan, 2017a). We refer to this probability as the *pooled expert choice probability*.

2.4. Model estimation

We used a two-level hierarchical Bayesian (HB) model for estimating the choice model coefficients (part-worths) deploying Sawtooth Software's CBC/HB System for Hierarchical Bayes Estimation (Orme and Chrzan, 2017b). HB weighs each expert's choices based on the variance of each individual's responses, therefore placing more weight on experts with "narrower" responses than individuals with more variant responses. In addition, the hierarchical structure of HB borrows information from all experts to improve individual expert's utility estimates. HB averages over experts with "narrow" (less variant) responses by pulling the responses towards the expert pool's mean and vice versa (Gelman et al., 2013). The smaller the expert sample the more HB will shrink parameter estimates towards the expert pool's mean. The full probability model in generalized form is the joint posterior distribution of all parameters as follows:

$$p(\alpha_n, D, \beta_n | y) \propto p(\alpha_n, D) p(\beta_n | \alpha_n, D) p(y | \beta_n, \alpha_n, D), \tag{4}$$

Where β_n is a vector of part-worth utilities of the nth expert, α is a vector of means of the distribution of individual part-worth utilities, and D is a matrix of variances and covariances of the distribution of part-worth utilities across individual experts (Orme, 2009b).[8]

On the right-hand side of Equation (4), the first probability statement is the hyper prior used for randomly drawing the parameters of the conditional normal priors, the second expression (Orme, 2009b, p. 62). The last expression is the joint likelihood of the observed data, y, following the multinomial distribution. Note, the likelihood only depends on the unknown parameter values β, α and D affecting y through β (Gelman et al., 2013).

Through application of the Monte Carlo Markov Chain (MCMC) algorithm and Gibbs sampling, we draw conditionally from the joint posterior distribution and simultaneously estimate the parameters α, β and D (Gelman et al., 2013). From these estimates we derive individual utility distributions (Johnson et al., 2003). After assessing convergence visually, the draws from the joint posterior distribution quantify uncertainty in each expert's utility estimate (Orme and Chrzan, 2017a).

[6] In the DCM literature, p_{ni}, is also commonly known as the preference share (Lancsar and Louviere, 2008).

[7] We use "raw" non-scaled utilities here. The scale factor, μ, is commonly used in the numerator and denominator as follows $e^{\mu\beta X}$, and is set to 1 during simulation, as further explained in section 2.5.

[8] We used the default settings for the CBC/HB software specifying initial values for, β,α, equal to zero and variance D equal to the identity matrix (Orme and Chrzan, 2017a, p. 146).

The part-worths are a compromise between the aggregate distribution of opinions across the sample and the individual's opinion and result in a conditional estimate of the expert's parameters. Part-worth utilities for each individual expert are estimated using HB with a burn-in of 10,000 iterations before 1000 random draws were saved.

We present results of estimating the choice model as the mean part-worth utilities for each attribute level rescaling to zero-centered utility differences, a common convention among academics and practitioners for standardizing part-worth utilities. Utilities are rescaled so that the sum of the utility differences between levels of each attribute, k, across all attributes, K, is equal to $100K$. Presenting the results of a DCM in this way is common in the resource management literature (Schroeder et al., 2018).

2.5. Sensitivity analysis

We conduct sensitivity analysis to investigate the marginal effect of each habitat attribute on experts' scenario choices (expert choice probabilities) by varying each attribute in turn while holding attributes constant at base-case levels of 50% vegetation cover, 5.5 mg/l DO, 400/m^{-2} prey abundance, and 20 piscivorous predators/acre. The *location of aquatic vegetation* attribute was set to be in all parts of salmonid habitat for the base-case scenario. This approach determines critical habitat characteristics that experts thought were essential for persistence of salmonids in elodea-invaded salmonid habitat and quantifies experts' toleration of trade-offs between levels of a given attribute.

We use Sawtooth's Choice Simulator and its "share of preference approach" to simulate individual expert choice probabilities for elodea-invaded salmonid habitat scenarios (Huber et al., 1999; Sawtooth, 2016a). The sensitivity analysis shows how the probability of an expert choosing an elodea-invaded scenario shifts in response to changes in attribute levels and relative to base-case assumptions, comparing it to the base-case habitat.

The share of preference approach assumes that experts carefully evaluate each salmonid habitat scenario. Another approach available via the Choice Simulator is called "randomized first choice" and assumes less observant choice behavior (Huber et al., 1999). We compare results from the two simulation approaches in section 3.2.

2.6. Coherence check

We assessed expert pool consistency and attribute importance by comparing risk-perception across expert groups. Based on responses to the risk rating exercise, we divided the expert pool into five groups. We then compared expert groups using two metrics of expert opinion. First, we estimated the *individual expert choice probability*, p_{ni}, that an expert selects an elodea-invaded habitat scenario. We also identified latent classes assuming equality in risk rating. Second, we looked at utility-derived relative attribute importance scores using individual experts' coefficients, β_n.

We prefer relative attribute importance scores over zero-centered utility differences because relative attribute importance scores allow for cross-attribute comparisons, revealing the influence of different attributes on expert choice more comprehensively. For example, if an attribute has twice the score of another attribute, experts believe it is twice as important for salmonid persistence in elodea-invaded salmonid habitat (Orme, 2010). Besides cross-attribute comparison, the scores can also be used for between-group comparisons showing how each expert group weighs the set of habitat attributes differently. Specifically, we are able to show evidence for potential pre-judgment if relative attribute scores are skewed, indicating respondents focused solely on only a few attributes, especially if the attribute of attention can be related to the risk rating response. In addition, the relative importance scores potentially answer whether experts considered framing information such as the background document prior to the elicitation.

The combination of the DCM and risk rating information offers multiple ways for comparing expert opinion and its consistency across individual experts and expert groups. We calculated the relative importance score for attribute k in group g as follows:

$$\mathrm{score}_{gk} = \sum_{n=1}^{n}\left(\frac{\max\beta_{nk} - \min\beta_{nk}}{\sum_{k=1}^{k}(\max\beta_{nk} - \min\beta_{nk})}100\%\right) \Bigg/ n, \tag{5}$$

Where β_{kn} is the mean of the posterior part worth-utility distribution for attribute k, estimated for each attribute level and specific to expert n, and maxβ_{kn} - minβ_{kn} represents the range of β_{kn} across all levels of an attribute k (Orme, 2010).[9] For each group, attribute importance scores are standardized to sum to 100, allowing for comparisons across groups.

3. Results

Of 111 experts contacted 56 responded, for a response rate of 50%. The sample is representative of the total initial expert pool (Table 1). Below, we first present what experts selected in the BYO exercise as their preferred habitat scenario followed by the results for the estimated DCM. We then present individual expert choice probabilities showing how likely experts were to select elodea-invaded habitat scenarios as supporting persistent salmonid populations. In a sensitivity analysis, we investigate how responsive expert choice probabilities are to varying habitat characteristics for scenarios with elodea invasion. Finally, we check for expert coherence by dividing the expert pool into five groups depending on answers to a risk rating exercise. We use choice probabilities and relative attribute importance scores as the metrics for between-expert and between-group comparison.

3.1. Build-your-own habitat scenarios

The results from the BYO scenarios in the ACBC approach reveal that three out of 56 experts favored elodea-invaded habitat over uninvaded habitat for supporting a persistent salmonid population. Experts indicated having salmonid species-specific knowledge for Sockeye (n = 11), Coho (n = 20), Chinook (n = 20), Dolly Varden (n = 4), and Humpback Whitefish (n = 1). Consistent with the assumption of unambiguous *a-priori* preference order in the choice design mentioned earlier, more experts selected low vegetative cover than high vegetative cover, higher DO concentrations rather than lower DO concentrations, more prey rather than lower prey amounts, and fewer predators rather than more predators (Table 3).

3.2. Choice model results

We analyze the DCM choice model to quantify experts' valuation of habitat attributes contributing to a persistent salmonid population and

Table 3
Build-your-own (BYO) habitat scenario frequency counts for attribute levels shown in brackets, n = 56.

Attribute	Uninvaded habitat		Elodea-invaded habitat	
	Level 1	Level 2	Level 1	Level 2
Vegetation cover	0% (36)	50% (17)	50% (3)	100% (0)
Dissolved oxygen (mg/l)	5.5 (8)	10.5 (45)	0.5 (0)	10.5 (3)
Prey abundance (mg/m^2)	400 (22)	600 (31)	30 (0)	3000 (3)
Piscivorous fish (#/acre)	5 (42)	20 (11)	20 (2)	35 (1)

[9] For an attribute with maxβ_{kn} = +15 and minβ_{kn} = −15 (zero-centered part-worth utilities), the numerator in Equation 3 would become 30.

Table 4
Model results showing attribute level coefficients affecting expert choices for salmonid persistence, the choice response variable. Coefficients are shown as rescaled zero-centered utility differences associated with each coefficient's posterior utility distribution, $n = 56$.

Attribute	Attribute Level	Mean, β	Standard deviation, β	Coefficient of Variation
State of habitat	Elodea-invaded	−129.95	40.49	31%
	Uninvaded	129.95	40.49	
Species	Sockeye	8.85	21.99	248%
	Coho	10.89	32.01	294%
	Chinook	−12.28	36.52	297%
	Dolly Varden	1.42	28.94	2038%
	Whitefish	−8.88	30.73	346%
Location of aquatic vegetation	Backwater	16.07	31.40	195%
	Entire system	−14.20	22.94	162%
	Lake	−1.87	24.97	1335%
Vegetation cover[a]	50% invaded	39.67	35.90	90%
	100% invaded	−39.67	35.90	
	0% uninvaded	0.35	38.44	10983%
	50% uninvaded	−0.35	38.44	
Dissolved oxygen (mg/l)[a]	0.5 invaded	−98.90	74.80	76%
	10.5 invaded	98.90	74.80	
	5.5 uninvaded	−52.67	53.77	102%
	10.5 uninvaded	52.67	53.77	
Prey abundance (mg/m^2)[a]	30 invaded	−35.05	29.08	83%
	3000 invaded	35.05	29.08	
	400 uninvaded	−10.59	19.01	180%
	600 uninvaded	10.59	19.01	
Piscivorous fish (#/acre)[a]	20 invaded	15.98	20.45	128%
	35 invaded	−15.98	20.45	
	5 uninvaded	48.06	46.39	97%
	20 uninvaded	−48.06	46.39	
No. of observations		560		
No. of experts		56		
No. of parameters		26		
Pseudo R^2		0.58		

[a] Salmonid habitat scenario-specific attribute levels dependent on state of habitat.

assessed agreement in these valuations. In Table 4, we present the mean and standard deviations associated with the posterior distributions of β coefficients (part-worth utilities) which affect the believed persistence of salmonids. Due to rescaling into zero-centered utility differences, any negative coefficients are interpreted as contributing less to expert choice whereas positive coefficients are interpreted as contributing more. It is important to note that the negative coefficients should not be interpreted as negative directional effects. Attribute levels with negative coefficients are not necessarily believed to be detrimental to salmonid persistence, but contribute less than positive coefficients to expert assessment. If the estimated mean of a coefficient is close to zero it indicates that experts on average are neutral regarding the attribute's contribution to expert belief about salmonid persistence in elodea-invaded habitat. The coefficient of variation (CV), equal to the standard deviation divided by the mean, provides a measure for the level of agreement among experts as to the influence of that attribute on choices. The pseudo R^2 of 0.58 suggests the model outperforms a similar model of chance in predicting expert choices (Table 4).

The state of habitat attribute had the largest effect on expert choice, with uninvaded habitat contributing the most to explain expert choices. There was also wide agreement among experts about this effect as shown by the relatively small CV for this attribute. Experts believed Coho and Sockeye Salmon to be more persistent than Chinook and Humpback Whitefish, shown by the negative coefficients. This result is consistent with studies that suggest large scale shifts in environmental conditions favor Sockeye and other salmonid species, while the outlook for Chinook is poorer (Adkison and Finney, 2003; Hare et al., 1999).

The *location of aquatic vegetation* attribute was one of the attributes with the lowest influence on expert choices shown by lower coefficients. The study, by design, assumed independence between fish species and the location of aquatic vegetation. Due to the varying life history and associated habitat use of salmonids, the role of aquatic vegetation depends on the species. For example, Coho Salmon rear in backwaters while most Sockeye Salmon rear in lakes or lake outlets. This assumed attribute independence prevented further investigation of more species-specific expert opinion conditional on the location of aquatic vegetation in salmonid habitat. Vegetation in backwater locations such as sloughs and other slow-moving water or in lakes was seen as beneficial whereas having vegetation everywhere was seen as detrimental to salmonid persistence (Table 4). The amount of vegetation cover was more important to experts in elodea-invaded habitat relative to uninvaded habitat as shown by the large difference in magnitude of the mean coefficients. However, expert opinion on the amount of vegetation in uninvaded salmonid habitat varied much more than over the amount of vegetation in elodea-invaded salmonid habitat. The CV for vegetation cover in uninvaded salmonid habitat is much larger than in invaded salmonid habitat (Table 4). This result is supported by literature showing that increasing vegetation cover can displace salmonids (particularly Chinook Salmon) from their spawning areas, yet uncertainty remains whether elodea threatens salmonid population persistence (Merz et al., 2008).

An attribute of noted importance was the amount of dissolved oxygen (DO), as demonstrated by the relatively large coefficients, whereas prey abundance and predator densities were less influential on expert choices (Table 4). Experts agreed more on the importance of DO level and prey abundance in elodea-invaded habitat than they agreed on this attribute for uninvaded habitat, perhaps indicating that DO and prey abundance become more important in elodea-invaded habitat (Table 4).

Higher predation levels in elodea-invaded habitat were believed to be less influential on salmonid persistence compared to lower predation levels in uninvaded habitat. This result suggests that experts have taken into account the refugia effect of vegetation cover in elodea-invaded habitat compared to native vegetation, partially offsetting higher predation (Casselman and Lewis, 1996). Experts, however, did not agree strongly on this matter as shown by the higher CV for predation in invaded relative to uninvaded habitat (Table 4).

3.3. *Probability of experts choosing invaded over uninvaded habitat supporting salmonid persistence*

We examine highly skewed expert opinion based on the probability of an expert choosing an elodea-invaded habitat scenario over an uninvaded scenario given base-case habitat attribute levels (Fig. 4). This result is consistent with the BYO exercise where a large group of experts ($n = 47$) is much less likely (25% chance) to choose a scenario with an elodea invasion that supported persistent salmonids. There is a small group of experts ($n = 4$) more or less likely (50% chance) to select a scenario with elodea invasion and another small group ($n = 5$) being much more likely (>80% chance) to select a scenario with an elodea-invasion (Fig. 4). Put differently, there was a 4% chance (median = 0.04, Fig. 4 denoted with a dashed line) that half of the experts in the pool ($n = 28$) selected an elodea-invaded habitat scenario to be supporting persistent salmonid populations. The mean was equal to 0.21 (Fig. 4 denoted with a dotted line).

The analysis also found that the predicted choice probabilities were robust to the simulation method. Fig. 4 shows a visual check comparing a histogram and density plot of individual expert choice probabilities using the randomized first choice and share of preference approaches.

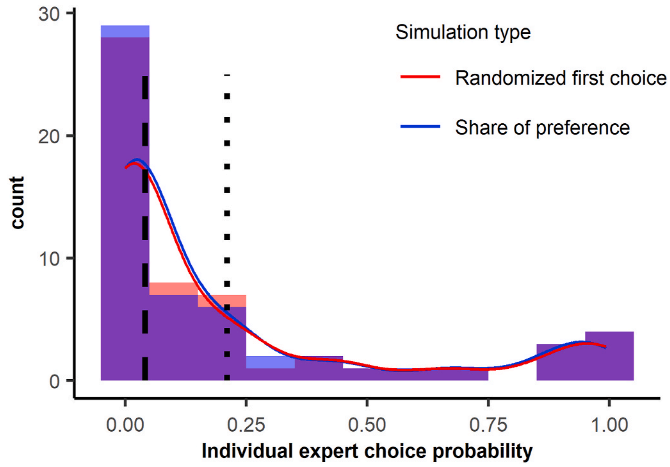


Fig. 4. Histogram of predicted individual expert choice probabilities for choosing elodea-invaded habitat over uninvaded habitat given base-case habitat assumptions. We show the sample median (dashed) and mean (dotted line). In blue and red we show densities (histogram) related to the two available simulation approaches used to predict choice probabilities. Purple indicates agreement of the two simulation approaches. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

3.4. Sensitivity analysis

In our sensitivity analysis we found that pooled expert choice probabilities (n = 56) are sensitive to varying habitat characteristics for elodea invaded salmonid habitat, especially DO. The pooled expert choice probability for elodea-invaded habitat can most steeply increase with increasing DO, moderately increase with increases in prey abundance, moderately decrease with increasing elodea cover and moderately decrease with increasing density of piscivorous fishes (Fig. 5). The steepness of the DO curve shows that any directional change in DO could greatly influence an experts' perception of persistent salmonids in elodea-invaded habitat, more so than any other attribute included in the design (Fig. 5).

3.5. Evaluating expert coherence and agreement

Combining information from the risk rating exercise and DCM and comparing this information across groups we found several inconsistencies in experts' responses and evidence of pre-judgment (Fig. 6) (Tversky and Kahneman, 1974). Group 1 rated elodea as having "significantly negative effects" on salmonids (n = 10), group 2 "moderately negative effects" (n = 35), group 3 "no effect" (n = 3), group 4 "moderately positive effects" (n = 1), and group 5 did not rate elodea's overall effects on salmonids (n = 7). No expert rated elodea as having "significantly positive effects" on salmonids (n = 0). Groups 1 and 2 had seven outliers (Fig. 6 upper left). Despite having rated elodea as negative, their choice probabilities for elodea-invaded habitat scenarios were much higher than would be expected, between $p_{in} = 0.7$ and $p_{in} = 0.98$ (Fig. 6). Similarly, the expert in group 4, who was the only one to rate elodea as having a moderately positive effect on salmonids, had a probability of choosing an elodea-invaded habitat scenario to support persistent salmonids equal to $p_{in} = 0.06$, unexpectedly low and inconsistent with the expert's rating (Fig. 6). Interesting to note, group 5

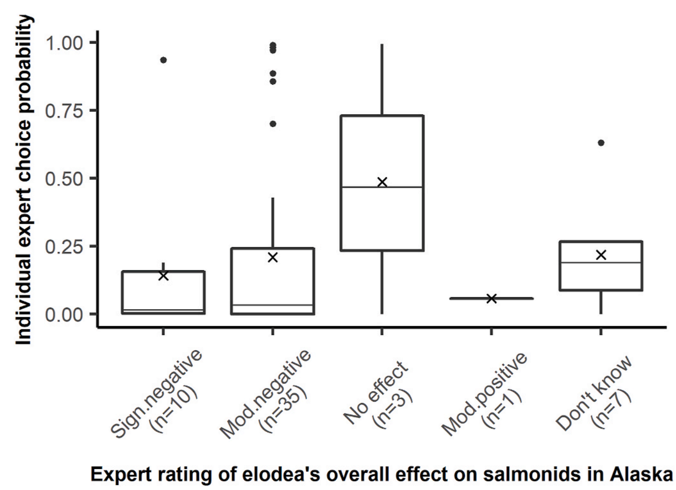


Fig. 6. Distribution of individual expert choice probabilities for choosing elodea-invaded habitat scenarios to support persistent salmonids. Distributions shown by experts' responses to a risk rating exercise. Lower and upper quartile (box), group median (bold line), group mean (x), and outliers (dots) are shown.

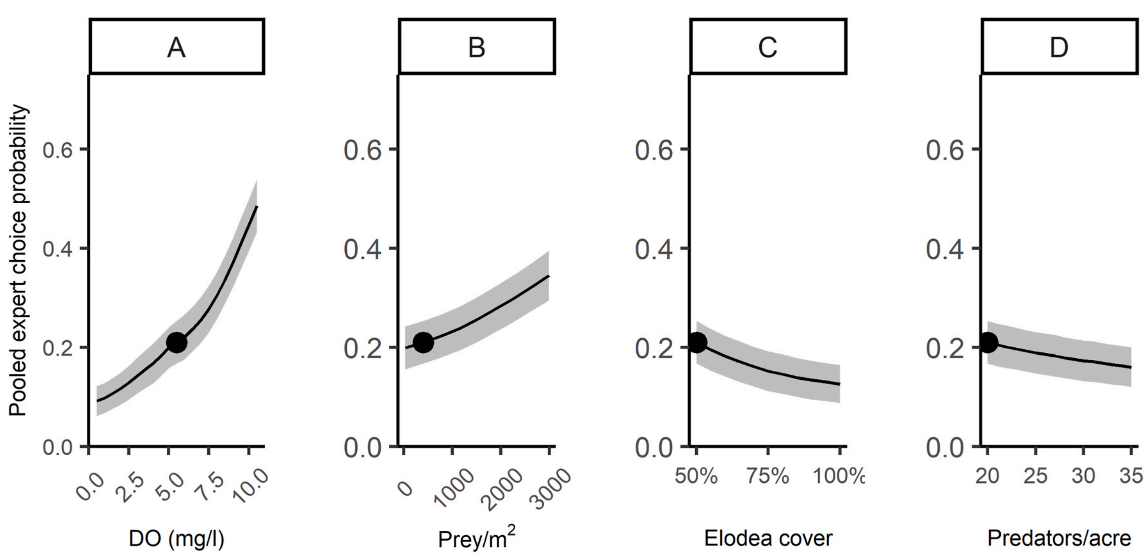


Fig. 5. Sensitivity of the pooled expert choice probability of selecting an elodea-invaded habitat scenario given changes in habitat attribute levels, sample mean (black line), 95% CI (shade), base-case (dot), for n = 56.

consisting of experts who were uncomfortable to provide a rating, had a median choice probability equal to 0.18. This probability is close to the mean choice probability of 0.21 for the entire expert sample. Except for its outliers, group 1, 2, and 3 showed consistent ratings compared with their choices in the DCM. The median choice probability for choosing an elodea-invaded scenario of group 1 (sig. negative) equalled 0.01, group 2 (mod. negative) 0.3, and group 3 (no effect) 0.47.

Group 3 provided evidence that suggests that collecting data on individual expert preferences is an important aspect of expert elicitation. While the risk rating indicated that experts in group 3 saw no effect of elodea on salmonids, the variation among experts' individual choice probabilities widely differed, more so than in any other group (Fig. 6). This result highlights the need to collect data on individual preferences beyond what a simple risk rating exercise could show. For managers, the additional information regarding how opinion varied despite the same "no effect" rating is important to take into consideration. It warrants a more detailed look at the drivers of such variability. Relative attribute importance scores can provide the necessary metric (Table 5).

Relative attribute importance scores are indicators for expert performance because they offer additional clues for why expert opinion varied (Table 5). For groups 1, 2, and 5, the state of habitat attribute (elodea-invaded or uninvaded) was the most significant attribute relative to other attributes. It suggests that experts may have only focused on whether scenarios showed invasions and thus ignored other differences in attributes, a common issue with DCM (Hensher, 2006). We observed this simplified attribute processing especially in group 1 where the state of habitat attribute was three times as important as the second ranked attribute, DO in uninvaded habitat. No other group had relative attribute importance scores that varied as much as group 1, suggesting that group 1 may have had opinions formed beforehand without considering elodea's ecological effects summarized in the background document (Supplementary File 1). Group 1's rating of significantly negative effects on salmonids supports this argument even though experts were consistent across their DCM responses and the risk rating exercise. It illustrates that consistency across different exercises is not sufficient for signaling expert quality. This suggests that the DCM and its individual expert coefficients can be used to signal pre-judgment when used in combination with other exercises.

DCM can also reveal unexpected inconsistencies. For example, experts in group 1 placed more importance on DO in uninvaded ecosystems (10.25) than invaded ones (8.96) (Table 5). For all other groups, DO in invaded salmonid habitat was more than twice as important than DO in uninvaded salmonid habitat (Table 5). In addition, group 1 experts weighed predation densities more heavily in uninvaded salmonid habitat than in elodea-invaded ones suggesting that the experts ignored synergies between Northern Pike and elodea described in the background document (Supplementary File 1). Groups 2 and 5 showed similar weighting among attributes not recognizing the elodea-pike interaction.

More than half of the expert pool, 62%, were part of group 2, rating elodea as having moderately harmful effects on salmonids. The similar magnitude in scores for the state of habitat (23.44) and DO in invaded habitat (20.33) tell us that experts mainly traded off the state of habitat attribute with dissolved oxygen (DO) in invaded habitat, suggesting that as long as DO levels were sufficiently high (Fig. 6, Table 5) these experts were more willing to choose elodea-invaded habitat than when DO levels were low.

The three experts in group 3 weighed attributes most equally among expert groups suggesting these experts paid attention to the ecological relationships at play, particularly for scenarios showing an elodea invasion. This result is consistent with this group having the longest completion times on average compared with the others, amounting to 50 min (Table 5). For these experts, DO for invaded habitat was ranked twice as important than the state of habitat attribute, 27.79 for DO and 16.4 for the state of habitat. Experts in group 3 also placed more importance on the salmonid species occupying the described habitat scenarios than any other group. This suggests that these experts not only paid attention to the ecological relationships at play but assessed them in the context of specific salmonid species. Also, the relative importance they assigned between the invaded and uninvaded scenario-specific attributes were consistent with expectations, showing higher importance scores for invasion-specific attributes compared to non-invasion-specific attributes (Table 5). This result indicates that experts in groups 3 and 4 considered synergistic elodea-pike interactions.

The sole group 4 expert shared many of the same qualities as the three group 3 experts in that several attributes were assessed as important, in contrast with the emphasis on just one or two attributes by groups 1, 2, and 5. This expert also placed higher importance on invasion-specific attributes compared to non-invasion-specific attributes as would be expected given the elicitation task (Table 5). Like experts in group 3, the expert in group 4 also placed highest weight on the DO in invaded habitat (25.24) followed by prey abundance (18.45). It is interesting to note that no other expert placed as much weight on the prey abundance attribute in elodea-invaded salmonid ecosystems. Research has found that macroinvertebrate communities can benefit from elodea invasions, justifying the expert's attention to this attribute (Schultz and Dibble, 2012). This result may be a reason for the expert's moderately positive rating of elodea's overall effects on salmonids. Despite these observations, the expert's probability of choosing an elodea-invaded habitat scenario for persistent salmonid populations ($p_{in} = 0.06$) was low given the expert's risk rating, and therefore illustrates inconsistency.

Group 5, who did not provide a rating, showed similar importance scores to experts in group 2 who expressed that elodea has moderately negative effects on salmonids in Alaska. This result illustrates that these experts were not necessarily outliers but that they were uncomfortable providing a rating, even though their choice data shows that they have substantial ecological knowledge consistent with that of other experts. For example, just as with group 2, experts in group 5 placed the most weight on the state of habitat attribute followed by DO in invaded ecosystems and like group 3 considered salmonid species more than other groups. Other ecological factors, such as the extent of vegetation

Table 5
Relative attribute importance scores explaining the choice of habitat scenarios by expert group.

	Expert rating of elodea's overall effect on salmonids				
	Sign. neg.	Mod. neg.	None	Mod. pos.	Don't know
Group ID	1	2	3	4	5
Expert count (% of expert sample)	10 (18%)	35 (62%)	3 (5%)	1 (2%)	7 (13%)
Mean completion time (min)	47	44	50	10	36
Attribute					
Salmonid species	7.51	7.26	8.82	5.45	8.37
Location of aquatic vegetation	5.29	3.96	3.73	7.93	8.38
State of habitat	[b]28.52	[b]23.44	16.40	16.24	[b]21.75
Vegetation cover[a] (invaded)	8.55	7.17	13.16	4.06	7.91
(uninvaded)	7.97	4.36	3.03	1.43	5.01
Dissolved oxygen[a] (invaded)	8.96	20.33	[b]27.79	[b]25.24	16.20
(uninvaded)	10.25	10.16	13.52	16.45	7.26
Prey abundance[a] (invaded)	6.45	7.27	8.10	18.45	5.53
(uninvaded)	3.14	3.02	1.26	1.69	5.06
Piscivorous fish[a] (invaded)	3.75	3.84	2.91	1.78	3.71
(uninvaded)	9.62	9.21	1.28	1.28	10.84

[a] Scenario-specific attribute, where levels are dependent on the state of habitat. The two most important attributes are shown in bold, with.

[b] Indicating the most important attribute. The importance scores sum to 100 for each group.

cover and local predator and prey populations, had some influence but were much less important to experts in group 5.

4. Discussion

Overall, the DCM results strongly suggest that habitat without elodea is more supportive of salmonid population persistence, however, expert opinion was highly skewed and widely distributed. This result is perhaps due to a relatively large group of experts with pre-judgment, the size of the expert pool, and the design of the DCM outcome variable. Below we discuss the relevance of results, application for decision making, and remaining methodological questions for future research.

The DCM allowed for performance evaluation by identifying inconsistencies and pre-judgment that we observed in a portion of the expert pool. We partially dealt with this issue by using HB for estimating the choice model, consequently pulling pre-judged responses towards the expert pool's mean. The enclosed background document likely did not minimize pre-judgment effects even though it was aimed at making experts aware of the current state of knowledge about elodea invasions. Future designs could include formal training prior to the elicitation. Also, one could measure the length of time respondents took to read the enclosed background document (if they even did) to further assess pre-judgment. Regardless, the benefits of adding formal training would need to be weighed against the costs of expanding the expert pool.

We show that DCM can expand the expert pool by including a larger and more inclusive range of expertise beyond local experts and experts from academia. Experts in group 5 demonstrate why expanding the expert pool may be beneficial. These experts were uncomfortable providing a risk rating, yet their DCM responses revealed substantial ecological knowledge consistent with that of other experts. In the absence of the DCM approach, several of these experts might have opted out of the survey, despite having expertise in the topic. Personal communication with study experts after the elicitation showed that being asked to define plausible expectations about an ecological outcome was much less intimidating for some experts than being asked to predict an outcome. In such circumstances, DCM can be more inclusive than other methods that limit and bias the expert pool towards individuals with academic experience. These experts may be more highly regarded by the academic community, less familiar with the local context, and more able to translate their knowledge into whatever form scientists require, most often quantities. The tendency to select experts based on expectations related to their academic qualifications, known as the social expectation hypothesis, can yield inconsistent elicitation performance (Burgman et al., 2011). Despite the 50% response rate there is a possibility that the responses are not representative of the available expertise.[10]

Expanding the expert pool also brings the statistical advantage of further averaging out the effects of outlier experts who perhaps were less rational in their response to the DCM. Furthermore, smaller, more exclusive expert samples are more likely to create doubt about whether the results are reliable for interpretation and decision-making compared to more inclusive and broader expert pools (Vanderhoeven et al., 2017). Research on sample sizes for expert elicitation demonstrates that expanding the expert pool to 25 or more improves elicitation outcomes (Maestas et al., 2014).

We recognize that a more balanced range of opinion could have been achieved by including indigenous knowledge bearers and naturalist enthusiasts, for example. Indigenous experts often possess complex ecological knowledge that in many circumstances is not being incorporated in ecosystem models (Huntington et al., 2013). Due to its binary and often visual response format (Hawley et al., 2008), DCM works well with a wide spectrum of populations including indigenous cultures (Miller et al., 2015), illiterate, and less formally educated rural residents in developing countries (Knowler et al., 2009). In this context, the ACBC customization is more engaging and relevant, outweighing costs associated with additional survey length compared to a more direct DCM (Cunningham et al., 2010).

Expanding the expert pool in conjunction with Bayesian estimation avoids the often difficult trade-off between retaining highly skilled experts while maintaining diversity in the expert pool (Albert et al., 2012; Drew and Perera, 2011). HB can measure individual expert opinion and aggregate it within groups for between-group comparison. HB also captures heterogeneous opinion and its associated individual-level uncertainty compared to weighting approaches that are either performance-based or apply equal weights (Bolger and Rowe, 2015).

Further, the choice of the discrete outcome variable could have also contributed to a skewed distribution of expert opinion. Salmonid population persistence represents a very clear but rather extreme ecological outcome. We recognize that managers and experts have significant interest in less extreme outcomes. The open-ended comments at the end of the questionnaire provide some useful insights. Of the 56 experts, 25 used the open-ended comment field to provide additional information about the reasoning related to their DCM choices. Of these, only four experts commented about the extreme outcome variable. For example, Expert 22: "I suspect the true response will be more a matter of moderate changes in fish production and survival that will result in either more or fewer fish, but not so extreme as they will cause population extirpation or prevent population viability" (Supplementary File 3). The fact that few experts commented on the extreme outcome variable is not to say that other experts did not have concerns about choosing an extreme outcome. Rather, few experts found the extreme outcome to be problematic.

Future study design can allow multiple avenues for less dramatic outcomes to be presented. We could alter the elicitation task (Fig. 3), for example by inclusion of an outcome variable in the form of an attribute (e.g. Wibbenmeyer et al., 2013) or requesting rating along best-worst scale instead of, or in addition to, binary choice (Hensher et al., 2005; Louviere et al., 2015). Another design variation could examine expert perspectives on changes in the abundance of salmonids rather than the persistence/extirpation dichotomy. While the advantages of such extensions are apparent, they come at the cost of putting an additional burden on participants in time and skill.

While this study establishes a proof of concept it could offer various methodological advantages that would need to be tested in future research. Distinct from many other approaches, DCM requires experts to consider the functional relationships between attributes and the discrete outcome variable. This characteristic may reduce availability bias, the tendency of people to consider examples that easily come to mind as being more representative of the truth than is the case. Furthermore, the occurrence of anchoring effects may be reduced through the binary response format that does not elicit quantities or probabilities. However, anchoring can still occur if experts pay closer attention to specific attributes they are more familiar with and pay less attention to attributes that are unfamiliar (Tversky and Kahneman, 1974). The interactive nature of the screener tasks and probing questions in the ACBC customization attempt to keep experts accountable for their responses.

We did not design this DCM elicitation as a comparison study, and such an investigation could provide valuable insights into developing DCM to complement other expert elicitation approaches. For example, DCM could serve as a pre-cursor to direct probability elicitation creating a systematic performance evaluation and screen prior to investing time into training experts. Many expert beliefs remain obscured by other approaches that are solely focused on eliciting quantities or probabilities. Yet performance metrics are important considerations for managers dealing with high uncertainty and complexity.

The DCM results are also more broadly applicable to specific management situations, informing monitoring efforts and ecological model building. For example, given that the relationships between attributes

[10] The study did not include non-respondents, and therefore did not explore non-response bias.

remain constant, the choice data can be used to predict expert opinion for any hypothetical environmental scenario described by the attributes. Ranked importance scores can inform variable selection and model building (Strange et al., 2019).

In the specific case of elodea and Alaska salmonids, DCM results can help managers discern when elodea invasions need to be managed to maintain salmonid populations. When there is uncertainty about the true impacts of a biological invasion, the ranked importance of habitat attributes can inform managers which habitat indicators are more or less critical to monitor.

5. Conclusions

Through analysis of data collected with the discrete choice method (DCM), this study informs resource management by providing a new understanding of the potential consequences of elodea establishment in Alaska conditional on a set of ecologically informed scenarios. It emphasizes several advantages and cases where DCM can contribute to expert elicitation in the ecological context. We demonstrated that DCM can quantify human preferences and trade-offs in experts' ecological assessments. The approach accounts for complexity while providing tractable ecological conclusions in situations of high uncertainty. Under these circumstances DCM offers a synthesis of expert data. DCM may also apply to a broader spectrum of experts, many of whom may be uncomfortable providing risk ratings or other more direct or predictive approaches. We showed how our approach can identify inconsistent experts and evaluate expert performance. We also show how the elicited data can be used to simulate expert opinion for a range of highly uncertain environmental management situations. The wider application of discrete choice methods for expert elicitation and decision making facilitates integration of broader ecological and largely non-quantitative knowledge into model building and expert selection. As such, DCM can serve as a precursor to traditional expert elicitation. Available software packages decrease the barriers for practitioners to apply the DCM approach for design, data collection and analysis.

Credit author statement

Tobias Schwoerer: Conceptualization, Methodology, Visualization, Investigation, Writing - original draft preparation, Data curation, Writing Joseph Little: Supervision, Writing, Reviewing and Editing Greg Hayward: Writing, Reviewing and Editing Writing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2020.110924.

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