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Evaluating the Ability of Specialization Indicators to Explain Fishing Preferences

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Understanding the predictive ability of recreation specialization to explain behavior is important for wildlife and fisheries management given the widespread use of specialization to capture diversity among outdoor recreationists. Using allocation of days among fishing opportunities in a discrete choice experiment, we studied the extent that specialization predicted preferences for attributes describing the opportunities. Latent class modeling revealed that three groups of anglers optimally captured preference diversity in our sample. To this base model, we sequentially added 11 metrics of angler specialization and used information theory to select the metric that best predicted group membership, namely centrality to lifestyle. Weaker evidence existed for the specialization dimensions "importance of catch," "specialized gear use," and a multidimensional self-classification approach, whereas indices of skill, media use, trophy fish, and harvest orientation were not supported. General specialization constructs such as centrality to lifestyle, therefore, might be best suited for predicting general fishing preferences and subsequent behaviors of anglers.

Keywords discrete choice, information theory, preference heterogeneity, recreational fishing, specialization

Introduction

Recreation specialization is an important framework for understanding diversity in outdoor recreation behavior. Bryan (1977) observed "a continuum of behavior from the general to the particular, reflected by equipment and skills used in the sport and activity setting preferences" (p. 175) in American trout anglers, concluding that recreationists may be grouped into angler types sharing specific values, beliefs, attitudes, and behaviors. Despite decades of research, however, operationalizing this multidimensional construct has eluded consensus (Scott & Shafer, 2001). Generally, research has relied on three main dimensions of specialization (Scott & Shafer, 2001). One is affective psychological commitment, such as centrality to lifestyle (Kim, Scott, & Crompton, 1997). A second dimension is cognitive development, including acquiring skills or knowledge (Salz & Loomis, 2005). A third dimension is behavioral involvement as revealed by indicators such as frequency of participation (Ditton, Loomis, & Choi, 1992). Psychological and behavioral metrics of involvement and commitment (Buchanan, 1985), and in particular the centrality to lifestyle construct (Kim et al., 1997), are perhaps the most widely used specialization constructs in outdoor recreation (e.g., Donnelly, Vaske, & Graefe, 1986; Dorow, Beardmore, Haider, & Arlinghaus, 2010), possibly because they can be applied across various activities, hence constituting "activity-general" metrics of specialization.

For consumptive leisure activities such as recreational fishing, researchers have developed a range of more "activity-specific" indicators or correlates of specialization that may explain specific preferences of anglers (Carlin, Schroeder, & Fulton, 2012). Some of these indicators relate to catch orientation, originally called consumptive orientation (Graefe, 1980), and includes the importance of (a) catching "something," (b) catching many fish, (c) catching a large trophy fish, and (d) keeping fish (Anderson, Ditton, & Hunt, 2007). In many angler populations, all four dimensions of catch orientation correlate with commitment and centrality. Bryan (1977), for example, observed greater importance placed on trophy fish among specialized trout anglers. More committed anglers have tended to be less consumptive than less committed anglers (Arlinghaus, 2007; Oh & Ditton, 2006). However, such relationships have not always held (Dorow et al., 2010; Salz & Loomis, 2005). Therefore, although angler specialization provides a sound basis for understanding diversity in fishing behaviors, there is much to learn from testing how well activity-general and activity-specific specialization indicators explain human dimensions issues, such as angler preferences for particular fishing opportunities. Only a few studies have linked specialization and choice of fishing opportunity (e.g., Carlin et al., 2012; Dorow et al., 2010; Oh et al., 2006). By understanding associations among specialization metrics and angler preferences and behaviors, one might potentially use specialization to predict their behavior without directly studying the concept.

To advance the field in this direction, improving operationalization of specialization is necessary. One approach for measuring specialization has relied on metrics of several subdimensions that are combined into a single composite index (e.g., Chipman & Helfrich, 1988; Fisher, 1997). One limitation of this approach is the burden that it places on respondents having to answer multiple questions/items (Needham, Sprouse, & Grimm, 2009). To alleviate this burden, many researchers have substituted a single salient subdimension (e.g., centrality to lifestyle, Dorow et al., 2010), or even a single metric (e.g., years of experience, Ditton et al., 1992), as proxies for the larger specialization construct, but this alternative approach does not capture the multidimensionality of specialization. More recently, a narrative, self-classification approach has been developed that combines multiple subdimensions in three or four narratives describing specialization categories, allowing respondents to select one that best defines their style of participation (e.g., Needham et al., 2009; Scott, Ditton, Stoll, & Lee, 2005). To some extent, self-classification solves the problem of respondent burden, while still capturing the multidimensionality of the specialization construct. Both self-classification and reliance on a single subdimension, however, inherently assume co-variance among various specialization dimensions and personal traits (Needham et al., 2009). Little research has evaluated the relationship between specialization and preferences (Carlin et al., 2012; Dorow et al., 2010; Oh et al., 2006) or systematically evaluated both quantitative and self-classification approaches to assess how well individual specialization indicators explain variation in angler preferences for catch and non-catch attributes of fishing opportunities. Following Bryan (1977), we expected clear relationships between specialization metrics and preferences for trip characteristics.

Our objective was to systematically test the ability of several metrics of specialization to predict variance in intended fishing behaviors among anglers in a regional fishery in Germany from their preferences for attributes describing available fishing opportunities (e.g., travel distance, expected catch). When framed in this context, preferences may be viewed as evaluative judgments in the sense of liking or disliking one object (e.g., fishing opportunity) relative to another (Scherer, 2005). Following the economic tradition of inferring preferences from behavior, we used a choice experiment (CE) to elicit intended (or stated) behavior from respondents. This approach produces estimates for activity-setting preferences of each aspect of a fishing opportunity (i.e., ecological, regulatory, social environments) by decomposing their influence on fishing opportunity selection. We then examined the degree that various specialization dimensions were related to angler preferences for catch and regulatory attributes that differentiate fishing opportunities. Although previous angler preference models have found that preferences vary with centrality to lifestyle among species-specific angler groups (Dorow et al., 2010; Oh & Ditton, 2006) and that importance placed on harvesting fish is predictably related to preferences for angling regulations (Carlin et al., 2012), limited research to date has presented an evaluation of the relative performance of multiple metrics of specialization (composite indices, single items, or self-classification) in predicting intention to fish.

Methods

The population of interest was anglers fishing in the German state of Mecklenburg-Vorpommern (M-V). This northeastern-most state of Germany borders the Baltic Sea and offers anglers diverse freshwater and marine fishing opportunities. Respondents were drawn from a random sample of M-V fishing license holders as described in detail in Dorow and Arlinghaus (2011). In total, 1121 anglers began a one-year angling trip diary program asking for trip-level information including target species, catch, harvest, and location. Throughout the year, quarterly telephone interviews with all anglers in the sample were conducted to keep participants motivated in the study, collect supplemental information on specialization, and clarify any emerging concerns or questions. To the 617 (58% response rate) diary respondents, a follow-up survey was mailed in October 2008 with a reminder postcard and replacement survey subsequently sent to nonrespondents. The questionnaire contained a CE and questions designed for measuring various specialization indicators. After accounting for item nonresponse across all specialization metrics, the final sample size for this study was 398 (65% of anglers who received the CE survey; 36% of anglers who began the study two years prior).

Operationalizing Specialization

Eleven indicators of specialization were developed from responses of the 398 anglers (Table 1). Activity-general indicators included behavioral commitment, centrality to lifestyle, and media use. Behavioral commitment consisted of a reliable composite index related to metrics of fishing participation, intensity, duration, and financial investment (Cronbach's $\alpha = 0.73$). Centrality to lifestyle was measured using a five-point agreement scale adapted from Kim et al. (1997). Principal component analysis (PCA) on the responses to this seven-item scale yielded a single reliable factor containing all items ($\alpha = 0.82$). Media use, including metrics of book, magazine, and website use (Chipman & Helfrich, 1988; Ditton et al., 1992) did not reliably combine with the general scale for measuring centrality, but the four items of media use were combined into a separate indicator ($\alpha = 0.63$).

Activity-specific indicators of specialization (Table 1) included skill and fishing knowledge of anglers from self-reported perceived skill relative to other anglers, relative catch per unit effort (CUE, weighted by proportion of days devoted to each species as revealed from diary entries), and a composite index of specialized gear use ($\alpha = 0.55$) adapted from McGurrin (1988). Catch orientation was measured with a mix of rating scales as attitudes toward the catch and consumptive aspects of fishing (adapted from Anderson et al., 2007; Graefe, 1980). Harvest orientation was also measured using motives for harvesting fish per trip (Beardmore, Haider, Hunt, & Arlinghaus, 2011), and actual harvest rates reported in the diary. Confirmatory factor analysis of the scale of catch and consumptive orientation yielded two separate indices. The first metric measured the overall importance ascribed by anglers to the process of catching fish ($\alpha = 0.70$) and the second, less reliable index focused on importance attached to catching large fish or trophies ($\alpha = 0.59$). To measure harvest orientation, three separate metrics emerged in our data. The first included three items from a fishing motivation scale (see Beardmore et al., 2011) related to harvest aspects of the experience ($\alpha = 0.62$) and the second and third metrics contained a single item from the catch orientation scale, "release most of the fish that I catch," and mean harvest rates (standardized for each species) reported in the diary.

The last metric of specialization involved a composite self-classification question that was presented to anglers only during the final follow-up mail survey approximately one year after the last telephone interview. Starting from Ditton et al.'s (1992) social world approach that proposed four levels of specialization ranging from "strangers" to "insiders," narratives incorporating multiple dimensions of specialization were developed for four archetypes: "casual," "active," "advanced," and "committed" anglers. Each narrative

TABLE 1 Composite Indices and Single Item Metrics of Specialization

Metric	Component/Item	Min	Max	*M*	*SD*	α
Activity-general indicators						
Behavioral indicators of commitment	Total fishing trips in M-V during the 12 months preceding the study	1	240	29.9	42.6	0.73[1]
	Total fishing trips taken on an average year	1	200	31.2	36.3	
	Total trips during study period (one year)	1	112	20.8	17.4	
	Proportion freshwater trips during study period	0.0	1.0	0.8	0.3	
	Total cost of licenses and tackle during study (expressed as% household income)	0.1	16.1	0.8	1.4	
	Total value of equipment (excluding boat, in Euro)	52	40,000	1,333.3	2,674.6	
Centrality-to-lifestyle[2]	I would lose a lot of my friends if I stop fishing	1	5	1.91	0.93	0.82
	If I could not fish, I would not know what else to do.	1	5	1.96	0.98	
	Because of my angling passion no time is left for other hobbies.	1	5	2.10	0.99	
	Most of my friends are connected to angling	1	5	2.28	1.12	
	Going fishing is the most enjoyable thing I can do	1	5	2.79	1.09	
	Other leisure activities do not interest me as much as angling	1	5	2.80	1.21	
	Most of my life revolves around angling	1	5	3.08	0.98	
Media use[3]	Angling books	1	5	2.53	1.00	0.63
	Angling magazines	1	5	2.60	1.08	
	Angling DVDs/videos	1	5	2.14	1.15	
	Websites about angling	1	5	1.72	1.00	
Activity-specific indicators						
Revealed skill (CUE)	Mean species-specific z-score of catch rate (weighted by effort allocated to each species)	−3.26	85.4	1.59	7.10	
Skill perception[1]	How would you judge your angling skills compared to other anglers?	1	4	1.94	0.60	
Catch importance orientation[2]	When I go fishing and nothing happens, I still keep pushing to catch something	1	5	3.49	1.19	0.70

(Continued on next page)

TABLE 1 Composite Indices and Single Item Metrics of Specialization *(Continued)*

Metric	Component/Item	Min	Max	*M*	*SD*	α
	I go fishing to earn respect from my angling friends through my catches	1	5	2.29	1.10	
	I go fishing because catches satisfy my ambitions.	1	5	2.72	1.16	
	I go fishing because catching fishes is very enjoyable for me	1	5	4.30	0.78	
	I go fishing because every caught fish improves my angling skills	1	5	3.06	1.14	
Trophy size orientation[2]	I prefer angling spots where I have the chance to catch trophy fish	1	5	3.30	1.15	0.59
	The bigger the fish the better the angling day	1	5	3.81	1.13	
	I prefer to catch 1 or 2 big fishes instead of catching 10 smaller ones	1	5	3.81	1.07	
Consumptive motivations[4]	To catch as many fish as possible	1	5	2.55	1.17	0.62
	To obtain fresh fish for a meal with family/friends	1	5	3.38	1.22	
	To generate a supply of fish in the freezer non-angling times	1	5	1.74	1.03	
Voluntary release orientation[2]	I release most of the fish that I catch	1	5	2.93	1.15	
Revealed retention behavior	Mean z-score of species-specific harvest rates	−0.83	7.90	.23	1.01	
Use of specialized gear[3]	High quality angling gear	1	5	2.58	1.18	0.55
	Special angling gear for specific fish species	1	5	2.81	1.28	
	Improving artificial baits	1	5	2.04	1.15	
	Personal angling diary	1	5	1.49	0.95	

Abbreviated table headers: Min – minimum, Max – Maximum, M – mean, SD – standard deviation, α – Cronbach's alpha

[1]based on reliability analysis of the *z*-scores for each item.

[2]Four-point scale as follows: 1 (less than others), 2 (equal to others), 3 (better than others), 4 (much better than others)

[3]Five point scale as follows: 1 (Strongly disagree), 2 (somewhat disagree), 3 (neutral), 4 (somewhat agree), 5 (strongly agree)

[4]Five point scale as follows: 1 (never), 2 (rarely), 3 (regularly), 4 (often), 5 (very often)

[5]Five point scale from 1 (not-at-all important) to 3 (somewhat important) to 5 (very important)

Part 4: Personal Information

16 **There are many different types of anglers. Which of the four angler descriptions below is most similar to yourself? Please note that not every criterium must be met, but select the description that generally describes you the best.**
(Please choose only one)

☐	Committed Angler	Someone for whom fishing is the central focus of life and whose social life revolves around angling. The committed angler fishes as often as possible, devoting most of his free time to angling related activities. Some characteristics of the ***committed angler*** may include: • Usually selects fishing waters based on their premium fishing quality even if they are distant. • Uses high-quality, species-specific fishing tackle and applies the latest innovations in fishing techniques and equipment: has an impressive collection of specialized fishing tackle. • Always targets a particular species on a given trip and tends to release any fish that are caught. • Typically continues to fish even when the fish do not appear to be biting • Uses many sources of information about fishing and may subscribe to angling magazines devoted to certain species or fishing styles
☐	Advanced Angler	Someone for whom fishing is the most important leisure activity and whose circle of friends includes many anglers. The advanced anglers fishes often, devoting a substantial fraction of his leisure time to fishing. Some characteristics of the ***advanced angler*** may include: • Usually selects fishing waters according to fishing quality and may travel long distances to particularly good waters • Prefers high quality fishing tackle and is aware of the latest innovations in fishing techniques and equipment: may have a considerable amount of fishing equipment, including some specialized equipment to target certain species. • Usually targets a particular species and often releases fish back into the water. • Rarely loses interest even when the fish are not biting. • Uses various information sources and may subscribe to a general angling magazine.
☐	Active Angler	Someone for whom angling is one leisure activity among many, and who occasionally goes fishing with a few friends. The active angler fishes regularly but also invests considerable time in other leisure activities. Some characteristics of an ***active angler*** may include: • Usually selects fishing sites that are relatively easy to access, often close to home. • Prefers common techniques and proven fishing tackle, and has some knowledge of the latest innovations in fishing techniques and equipment; has a moderate amount of fishing equipment, primarily consisting of general-purpose tackle • Often targets a particular species of fish on a given day, and usually takes home any legal fish that are caught. • Occasionally loses interest when the fish do not appear to be biting • May use easily available general angling media and buy the occasional issue of an angling magazine.
☐	Casual Angler	Someone for whom fishing is not an important leisure activity and whose social life does not involve angling. The casual angler fishes only occasionally and spends much of his leisure time pursuing other activities. Some characteristics of a ***casual angler*** may include: • Almost always selects fishing waters based on convenience and easy access. • Prefers common techniques and proven tackle and us not aware of the latest innovations in techniques and equipment; has a small amount of general fishing tackle. • Primarily targets whatever species is biting on a given trip, and harvests all fish that are legal to keep. • Often loses interest when the fish are not biting well. • Very rarely uses information in the public domain about fishing.

FIGURE 1 Specialization self-classification question from the follow up survey.

included statements related to centrality to lifestyle, behavioral commitment, skill, catch orientation, media, and specialized gear use (Figure 1). Respondents simply chose the single narrative best describing themselves. In total, 74 individuals (20%) identified themselves as casual anglers and 212 (55%) described themselves as active. Given that only

10 individuals (3%) self-classified as committed anglers, they were combined with the 82 (22%) advanced anglers for further analysis. These types of self-classification approaches are gaining prominence in the literature because they reduce burden on respondents of answering several long scales, but the relationship of this index with intended fishing behavior is unknown.

Modeling Intended Behavior

The purpose of the CE was to understand supply factors relevant for selecting a fishing opportunity. In this method, respondents jointly evaluate salient attributes, and preferences for these attributes and attribute levels are derived from a statistical model. Here, the alternatives of the CE described hypothetical angling opportunities for M-V (Figure 2). Each opportunity was described by several attributes including trip outcomes (catch: main target species, expected number of fish caught, their average size, and the size of the largest; social: number of other anglers seen while fishing as a measure of reported encounters), harvest regulations (minimum-size limit, daily bag limit) and cost (license fees to fish within the state of M-V, one-way travel distance). An additional attribute simulated the availability of stock assessment data to inform anglers about the biological sustainability of fishing at that location. All attributes were specified at four levels except license fee (eight levels) and were systematically varied in an orthogonal fractional factorial design of 128 choice sets (each containing three fishing experiences) while still allowing estimates of main effects (Raktoe, Hedayat, & Federer, 1981). In each choice set, respondents were asked to allocate ten hypothetical angling days among six alternatives—three angling opportunities as described above and three base alternatives: (a) fishing elsewhere in M-V

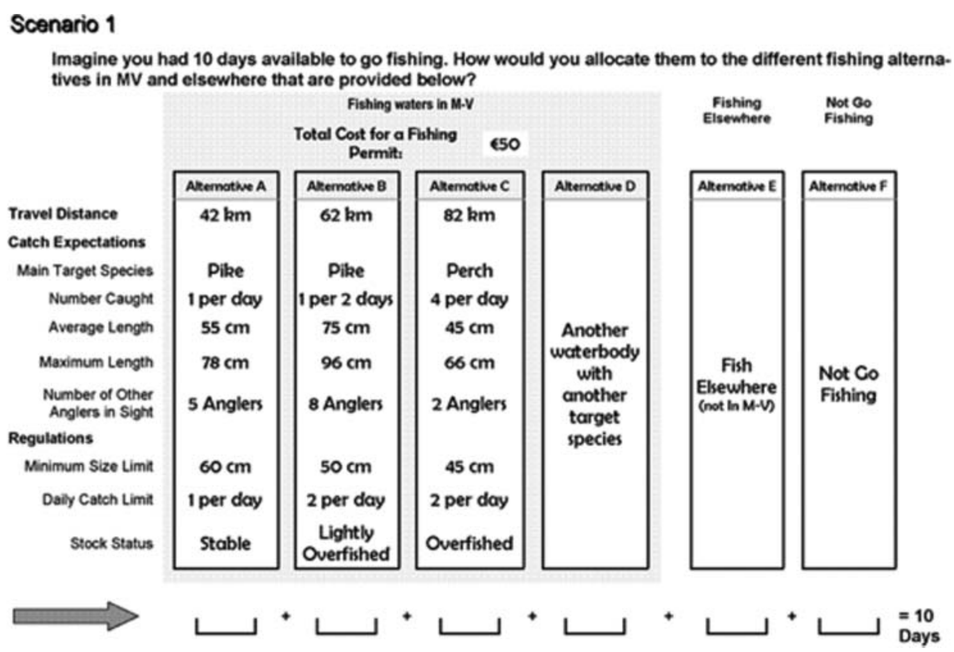

FIGURE 2 Example of a stated preference choice task shown from the follow-up mail survey. Several attributes were tailored to each respondent based on their preferred species and travel habits. Catch attributes were chosen around species-specific averages and standard deviations (see Table 2).

for another species, (b) fishing outside M-V, and (c) not fishing. To reduce the burden on each respondent, an additional orthogonal variable grouped the choice sets into 16 blocks each consisting of eight choice sets. One block was randomly assigned to each respondent.

Given the diverse fishing opportunities in M-V and the general nature of our angler sample (i.e., any type of recreational angler), we tailored the available species to each individual respondent from personal diary information, and based all trip outcome and regulatory attributes around species specific distributions from trips recorded in the diary (Table 2). We confined the survey to the eight species and two species groups that were targeted by anglers on more than 96% of their recorded trips.[1] For each species, we calculated means and standard deviations for catch characteristics and number of anglers seen when fishing from all diary respondents,[2] and thus defined realistic attribute levels for the CE based on these statistics (Table 2). Similarly, we developed standardized levels for regulatory attributes (minimum-size limits and daily bag limits) from current or historic regulations applied to each species in the study area. Each choice set contained personalized fishing opportunities of each angler's top three targeted species, with associated travel distances based on their personal average travel characteristics. Two attributes required no tailoring to individual respondents, namely license costs and stock status levels. All final attribute levels were determined following extensive pretesting with anglers from local angling clubs in M-V to ensure saliency and behavioral relevance.

Analysis of the Choice Experiment

The CE data were analyzed with a latent class choice model (Swait, 1994). The model is consistent with Random Utility Theory (McFadden, 1974), which suggests that people seek to maximize their well-being (utility) when choosing one alternative, such as a fishing opportunity, over another. Following a long tradition in economics (Lancaster, 1966), we assumed that respondent well-being arises from linear combinations of attributes defining an alternative and the associated preferences for these attributes. The latent class choice model estimates angler membership in different groups (classes) and preferences of each group for attributes and associated levels describing a fishing site. Unlike methods relying on a priori grouping of respondents into distinct segments (e.g., Dorow et al., 2010), latent class models statistically determine classes to maximize differences in their preferences. Following Swait (1994), we assumed that class membership probabilities and site selection followed conditional logit models of the form:

$$P_{ni} = \frac{e^{\alpha_{nl}+\sum_{c=1}^{C}(\beta_{nlc}*z_{nlc})}}{\sum_{l=1}^{L}(e^{\alpha_{nl}+\sum_{c=1}^{C}(\beta_{nlc}*z_{nlc})})} * \frac{e^{\alpha_{ni}+\sum_{a=1}^{A}(\beta_{nia}*z_{nia})}}{\sum_{i=1}^{J}(e^{\alpha_{ni}+\sum_{a=1}^{A}(\beta_{nia}*z_{nia})})} \quad (1)$$

where the probability of individual (n) choosing alternative i from J total alternatives depends on the product of two logistic functions. The first function governs the probability

[1]Atlantic cod (*Gadus morhua*), Atlantic herring (*Clupea harengus*), the group of marine flatfish species (e.g., founder – *Platichthys flesus*), garfish (*Belone belone*), common carp (*Cyprinus carpio*), a group of coarse fish species (i.e., small bodied cyprinid species such as roach, *Rutilus rutilus*), European eel (*Anguilla anguilla*), Eurasian perch (*Perca fluviatilis*), northern pike (*Esox lucius*), and zander (*Sander lucioperca*).

[2]A table presenting the descriptive statistics by which realistic attribute levels were defined for each species may be obtained from the corresponding author.

TABLE 2 Standardized Attribute Levels Used in the Discrete Choice Experiment of Fishing Site Selection for German Anglers

Trip costs	Expected outcomes	Fishery regulations and stock status
Annual license costs[1]	Number caught	Minimum-size limit
10€ ($14U *SD*; 1.25 *SD* $<$ mean)	0.4 *SD* $<$ species mean	None
25€ ($35 U *SD*; 1.0 *SD* $<$ mean)	Species mean	Current/Historic
60€ ($84 U *SD*; 0.5 *SD* $<$ mean)	1 *SD* $>$ species mean	20% larger
95€ ($133 U *SD*; current mean expenditure)	1.5 *SD* $>$ species mean	40% larger
130€ ($182 U *SD*; 0.5 *SD* $>$ mean)	Maximum expected size	Daily bag limit[3]
165€ ($231U *SD*; 1 *SD* $>$ mean)	0.5 *SD* $<$ species mean	None
235€ ($329U *SD*; 2 *SD* $>$ mean)	0.5 *SD* $>$ species mean	2 fish more
270€ ($378U *SD*; 2.5 *SD* $>$ mean)	2 *SD* $>$ species mean	Current
	3.5 *SD* $>$ species mean	2 fish less
One-way travel distance	Average expected size[2]	Stock status
Current Personal Mean	1.75 *SD* $<$ maximum size	No Information
Personal mean +20 km	1.3 *SD* $<$ maximum size	Stable (no risk of collapse)
Personal mean +40 km	0.9 *SD* $<$ maximum size	Lightly overfished (50% chance of collapse in the next 25–50 years)
Personal mean +60 km	0.5 *SD* $<$ maximum size	Overfished (50% chance of collapse in the next 2–5 years)
	Number of other anglers seen	
	0.5 *SD* $<$mean for species	
	Mean number for the target species	
	1 *SD* $>$mean for species	
	2 *SD* $>$mean for species	

SD = Standard Deviation of population-level distribution. Expected outcomes levels were based on the species-specific distributions of catches by the entire sample, while travel distance was personalized to each angler individually.

[1]U.S. dollar amounts are based on the mean exchange rate in October, 2008 (1€ = $1.40).

[2]Average expected size was expressed relative to the maximum expected size presented in the profile. Consequently, $4 \times 4 = 16$ possible values were shown for each species.

[3]For species with no current bag limit, the 'current' bag limit was set as the current average number caught, which then varied by ± 0.5 *SD*. Most species have a current daily bag limit of 3 fish.

that the individual belongs to class l (of L classes) as a function of a constant (α_{nl}) and parameter coefficients (β_{nlq}) of C angler characteristics (x_{nlc}). In our case, these characteristics were defined by our specialization metrics. The second logistic component of the model governs the probability that members from a class l will select an alternative. This selection is influenced by the class' preferences for attributes defined by an alternative specific constant (α_{ni}) and parameter coefficients (β_{nia}) along with the attributes and level of attributes (z_{nia} e.g., catch, management regulations). Latent class parameter functions were estimated using maximum likelihood estimation in Latent Gold Choice 4.5 software (Vermunt & Magidson, 2005).

To indicate their fishing preferences, respondents allocated ten fishing days among the alternatives in each choice set (Figure 2). Each alternative (i.e., fishing opportunity) was then treated as an observation, whose replication weight was equal to the frequency of being chosen (Vermunt & Magidson, 2005). We coded all numeric attributes as linear effects, whereas categorical attributes were effects coded (i.e., average effect of an attribute was set to zero).

Model Selection

The relationship between each of the 11 specialization indicators and the latent classes was explored in separate predictive models where the specialization indicators were treated as covariates to predict class membership. Selection of the best-fit model was conducted using an information-theoretic approach (Burnham & Anderson, 1998), which, given a data set and suite of competing models, formally examines the relative loss of information associated with each model as measured by the Akaike Information Criterion (AIC; Akaike, 1974). The best model is the one that loses the least information. Given that this approach jointly tests evidence among a set of competing models, proponents of this approach consider statistical tests associated with null hypothesis testing to be irrelevant (Burnham & Anderson, 1998).

Given our relatively small sample and reasonably large number of estimated parameters, we used the related criterion of AIC_C (Hurvich & Tsai, 1989):

$$AIC_c = -2\,hbox\,LL + 2K\left(\frac{N}{N-K-1}\right) \tag{2}$$

where N is sample size, LL is the log likelihood, and K is the number of estimated parameters. The model with the minimum AIC_C has greatest support (Burnham & Anderson, 1998). One usually reports the AIC_C along with the difference between the AIC_C for a model and the minimum AIC_C (Δ) and the probability (Akaike weights, w) that any given model in the set of J models is best, as follows:

$$w_i = \frac{e^{-\frac{1}{2}\Delta_i}}{\sum_{j=1}^{J} e^{-\frac{1}{2}\Delta_j}} \tag{3}$$

To limit the number of models under consideration, we used a two-stage approach for model selection. First, we used information theory to determine the appropriate number of latent classes to use for subsequent analyses.[3] Second, we estimated separate models

[3]For brevity, Table 3 presents models specifying only one to five classes, as these were sufficient to establish the best-fit model; however, the authors assessed models including up to 20 classes,

TABLE 3 Selection of Latent Class Preference Model

Classes	*N*par	LL	AIC_C	R^2	ΔAIC_C	*w*
3	56	−4756.2	9643.1	0.15	0.00	100.00%
4	75	−4745.9	9677.2	0.16	34.1	0.00%
5	94	−4729.1	9705.1	0.17	62.1	0.00%
1	18	−5067.3	10172.5	0.04	529.4	0.00%
2	37	−4830.5	9742.9	0.12	99.8	0.00%

All models are based on the same attribute specification, and are limited to anglers without any missing values.
$N_{\text{anglers}} = 398$; $N_{\text{choicesets}} = 3007$, LL – log likelihood, AIC_C – corrected Akaike Information Criterion, R^2 – McFadden's R^2, ΔAIC_C – Change in AIC_C, w – AIC_C weight.

to test each of the 11 specialization measures' ability to predict class membership, and thus, diverse angler preferences. These 11 models were pooled for evaluation with the base model containing the same number of latent classes, but no predictors of class membership. To supplement these analyses, socio-demographic characteristics (age, income, education, gender, average distance traveled to go fishing) of the latent classes were compared using analysis of variance (ANOVA) and χ^2 tests.

Results

The first stage of analysis involved selecting the optimal number of latent classes needed for capturing diverse preferences observed in our data. Overwhelming support ($w \approx 100\%$) emerged for the three-class model over the other models given our data (Table 3). Given this three-class model, the second stage examined the explanatory power of each of the 11 specialization metrics to predict respondent membership in the three classes. Each metric was included separately in models that were evaluated alongside the three-class model with no specialization measure. The centrality to lifestyle model ($w = 77\%$, Table 4, Figure 2) emerged as the best model given our data. Only three other models (self-classed specialization, catch-importance orientation, specialized gear use) had more support than the model with no metric of specialization. The models using metrics of perceived skill, actual skill (effort weighted CPE), media use, consumptive motivations, trophy and harvest orientations, harvest rate, and behavioral commitment performed worse than the model without specialization, indicating that these metrics contributed to information loss.

Class 1 comprised 58% of the sample, with membership probabilities increasing with centrality to lifestyle and importance of catch, and decreasing with specialized gear use. Probability of membership in this group was also higher when anglers self-classified themselves as advanced or committed (Figure 3). Class 2 accounted for 33% of the sample, with probability of membership decreasing as centrality to lifestyle and catch importance-orientation increased. Individuals reporting more frequent use of specialized gear and/or self-classifying as either active or casual, were also more likely to be members of Class 2. Class 3 only contained 9% of the sample. Membership in this class was largely independent of centrality to lifestyle, catch-importance orientation, or specialized gear use. However, Class 3 members were more likely to self-classify as advanced or committed anglers than were others.

consuming all available degrees of freedom. These additional results may be obtained from the corresponding author.

TABLE 4 Model Selection to Predict Membership in Each of Three Latent Classes Using Specialization Indicators as Covariates

Specialization covariate(s)	*N*par	LL	AIC_C	ΔAIC_C	*w*
Centrality-to-lifestyle	58	−4750.1	9636.4	0.0	76.98%
Catch importance orientation	58	−4753.0	9642.2	5.8	4.24%
Self-classification	60	−4750.3	9642.3	5.9	4.03%
Specialized gear use	58	−4753.3	9642.9	6.5	2.98%
Base (no specialization covariate)	56	−4756.2	9643.1	6.6	2.84%
Skill perception	58	−4753.5	9643.1	6.7	2.70%
Media use	58	−4754.1	9644.3	7.9	1.48%
Revealed skill (CPUE)	58	−4754.5	9645.2	8.7	0.99%
Consumptive motivations	58	−4754.5	9645.2	8.8	0.95%
Trophy size orientation	58	−4754.5	9645.3	8.8	0.95%
Behavioral indicators of commitment	58	−4754.8	9645.7	9.3	0.74%
Voluntary release orientation	58	−4754.9	9646.1	9.6	0.63%
Revealed retention behavior	58	−4747.1	9646.6	10.1	0.49%

$N_{anglers} = 398$; $N_{choicesets} = 3007$, *N*par – number of parameters, LL – log likelihood, AIC_C – corrected Akaike Information Criterion, ΔAIC_C – Change in AIC_C, *w* – AIC_C weight.

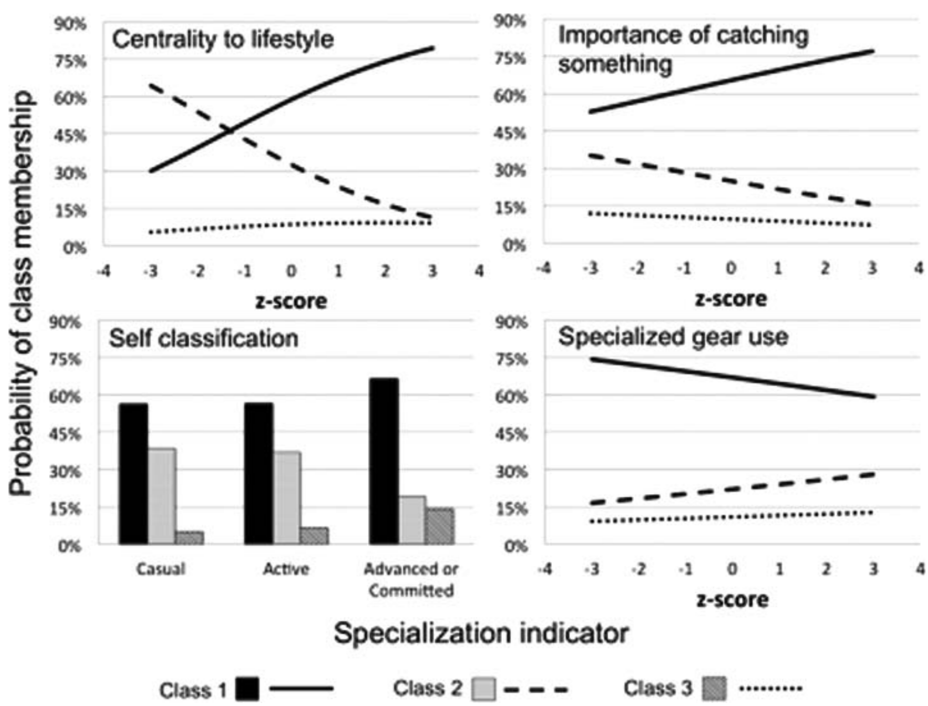

FIGURE 3 Latent class membership predicted by four metrics of specialization. For any given value on the x-axis, the probabilities on the y-axis sum to 100%.

The three latent classes differed in the magnitudes of many of their preference coefficients for attributes describing M-V fishing site experiences (Table 5). Class 1 anglers clearly preferred the fishing alternatives within the state of M-V, and demonstrated the lowest sensitivity to license costs for fishing within the state, indicating they were most committed to fishing in M-V. These anglers were also characterized by a moderately high willingness to travel, which is an indication of a high value placed on fishing within M-V. Members of Class 1 attributed the least importance to the average size (expected length) of fish caught, with comparatively more importance placed on the maximum size of caught fish. They also showed the most tolerance for seeing other anglers on the water (i.e., encounters). Class 1 was also only moderately responsive to changes in stock status, falling between Classes 2 and 3.

Class 2 anglers were characterized by the lowest centrality and preferred the base alternative of "not fishing" over "fishing," indicating less overall interest in the activity. They were also highly sensitive to both license fees and travel distance, and showed the least preference for a particular target species. For this class, the number of fish caught was more important, whereas the size of the largest fish was less important than these attributes were to the other classes. Class 2 anglers were most averse to the bag limit of one fish and exhibited the strongest preference of all angler classes for sites reporting good stock status.

Class 3 anglers preferred to fish outside M-V. Like Class 2 anglers, Class 3 anglers were less willing to pay high license fees, but they were willing to travel farther to access more distant sites within the study area. They were most influenced in their site choices by strong preferences for a single target species. Of all the latent classes, this angler type placed the least importance on the number of fish caught and most importance on the average size of fish caught. Class 3 anglers were also most sensitive to encounters, but were least sensitive to information about overfishing.

Taken together, these results suggest that Class 2 anglers are least specialized. The other two classes may be more specialized, depending on the metric by which they are classified. Class 1 is characterized by high centrality to lifestyle, whereas Class 3 represents a multidimensional specialization group as captured by the self-classification metric.

Discussion

We modeled intended behavior revealed by fishing days allocated among fishing opportunities in a discrete choice experiment to evaluate the ability of several specialization metrics to explain differences in preferences within our sample of German anglers. Consequently, we tested the internal consistency of the relationship between various dimensions of specialization behavioral intentions. Diverse fishing preferences in our sample were mainly driven by varying preferences for general attributes of fishing such as cost and travel, with much less diverse preferences among classes for catch or management attributes of the fishing experience. Not surprisingly, activity-general measures of angler specialization, in particular centrality to lifestyle, rather than activity-specific measures such as trophy fish orientation, best captured the variation in fishing preferences from the latent class models. This finding is consistent with the principle of "object specificity" (Smith & Swinyard, 1983) as an activity-general specialization metric best explained variation in general fishing preferences.

Among the 11 metrics of specialization, centrality to lifestyle (Kim et al., 1997) was especially suitable to predict angler preferences for available fishing opportunities in the context of a regional, multispecies fishery. This result supports previous studies using centrality to lifestyle for *a priori* segmentation of recreational anglers (Dorow et al., 2010; Oh & Ditton, 2006). In our study, centrality to lifestyle distinguished among individuals

TABLE 5 Latent Class Preference Model for Fishing Intentions of Differently Specialized German Anglers

			Class 1[1]		Class 2[2]		Class 3[3]	
Attribute	Type	Unit	β	SE β	β	SE β	β	SE β
Intercept	Nominal	fish in M-V	0.79	0.073	−0.194	0.094	−0.578	0.186
		fish outside M-V	−0.286	0.092	−1.181	0.131	1.074	0.149
		not fish	−0.504	0.111	1.376	0.086	−0.496	0.18
Cost	Numeric	10 € increment	−0.029	0.01	−0.118	0.01	−0.132	0.023
Distance	Numeric	20km increment	−0.105	0.016	−0.226	0.029	−0.085	0.06
Effort to species	Numeric	percent	0.497	0.171	0.412	0.285	1.365	0.605
Fish number	Numeric	*SD* from species mean	0.133	0.043	0.156	0.076	0.093	0.164
Average expected length	Numeric	*SD* from species mean	0.028	0.057	0.181	0.102	0.412	0.229
Maximum expected length	Numeric	*SD* from species mean	0.114	0.028	0.046	0.049	0.106	0.103
Expected number of anglers seen	Numeric	*SD* from species mean	−0.072	0.035	−0.104	0.061	−0.132	0.135
Minimum-size limit	Nominal	no limit	0.009	0.057	0.023	0.098	0.007	0.214
		current/historic	0.041	0.057	−0.061	0.101	−0.143	0.225
		20% larger than current	0.015	0.058	−0.005	0.103	0.084	0.21
		40% larger than current	−0.064	0.059	0.043	0.103	0.052	0.217
Daily bag limit	Nominal	no limit	0.028	0.057	0.063	0.104	−0.134	0.231
		2 more / 0.5 *SD* higher than mean catch	0.057	0.057	0.103	0.098	0.197	0.218
		current bag limit / current mean catch	0.018	0.058	0.037	0.099	0.048	0.208
		2 less / 0.5 *SD* less than mean catch	−0.102	0.059	−0.203	0.107	−0.111	0.224
Stock status	Nominal	no Information	0.095	0.056	0.064	0.098	0.011	0.222
		good	0.317	0.055	0.391	0.092	0.319	0.192
		lightly overfished	−0.064	0.059	0.007	0.103	−0.089	0.226
		overfished	−0.348	0.062	−0.461	0.117	−0.241	0.249

β– parameter estimate, SEβ– standard error of the estimate
[1]Class size = 58.3%; $R^2 = 0.025$; $R^2(0) = 0.073$.
[2]Class size = 33.1%; $R^2 = 0.118$; $R^2(0) = 0.252$.
[3]Class size = 8.6%; $R^2 = 0.091$; $R^2(0) = 0.209$.

differing in their willingness to pay license fees and travel, confirming that high-centrality anglers derive greater wellbeing from the fishing experience than do low-centrality anglers (Ditton & Sutton, 2004; Dorow et al., 2010; Oh, Ditton, Anderson, Scott, & Stoll, 2005). Although centrality to lifestyle has been linked to diverse preferences for costs, catch expectations, and management preferences (Dorow et al., 2010; Oh & Ditton, 2006; Oh et al., 2005), our study corroborates these findings within a novel statistical framework. Accordingly, Class 1 anglers were more likely to exhibit higher scores for centrality to lifestyle and consistent with Oh et al. (2005), these anglers also showed higher acceptance of license fees despite no discernible difference in mean household income. Conversely, Class 2 anglers had lower centrality to lifestyle scores, consistent with tendencies to choose the non-fishing alternative and low willingness to pay or travel to fish and indicating less attachment to fishing and fewer benefits derived from fishing relative to other leisure activities. Finally, Class 3 anglers' stronger preference for fishing outside the study area and for alternatives presenting highly preferred target species indicated that this group may exhibit the highest species-related resource dependency and be most species-specialist in the spirit of Bryan (1977).

Three additional metrics of specialization also improved predictions of latent class membership relative to the inclusion of no metric, although to a much lesser extent than centrality to lifestyle. Of these three, the lower performance of the narrative self-classification approach compared to centrality to lifestyle is worth discussing because this narrative included explicit statements about involvement and centrality to lifestyle. The various narratives, however, also contained several activity-specific dimensions of specialization whose models did not rank well and when combined in a single self-classification statement, may have diluted the effect of the single most important subdimension (i.e., centrality to lifestyle). This result suggests a possible weakness of the self-classification approach, as its performance is limited by the degree that the included subdimensions covary within each specialization level. Lack of covariance among activity-general (e.g., centrality) and activity-specific (e.g., trophy fish orientation) measures of specialization can be expected to reduce the value of narrative specialization constructs to predict attitudes, preferences, and behaviors of recreationists. Moreover, although the ease of assessment in surveys is a major advantage, self-classification reduces variance by forcing a few groups rather than allowing a researcher to treat specialization as a scalar variable in statistical models. Despite these limitations, the use of self-classification methods is becoming more popular (e.g., Kerins, Scott, & Shafer, 2011; Needham et al., 2009; Scott et al., 2005). Therefore, further work is warranted to determine the range of behaviors and preferences for which a narrative self-classification approach provides salient information, and to determine the important dimensions of specialization necessary for inclusion in the narrative description to maximize predictive capabilities given a particular context.

The other two models that outperformed the one excluding a metric of specialization used catch orientation and gear use covariates for explaining membership of anglers to classes. Both specialized gear-use and catch importance are activity-specific components of angler specialization (Fisher, 1997) but were operationalized here to be independent of angler target fish species. Therefore, they retained some level of generality that may explain their ability to predict class membership in our generic choice. Specifically, members of the more specialized Class 1 placed more importance on catching "something." Qualities of catch desired by anglers shifted slightly from high catch rates among less specialized anglers (Class 2) to size and challenge aspects for more specialized anglers in Classes 1 and 3. These patterns corroborate earlier specialization research (Beardmore et al., 2011; Bryan, 1977), but not all past research (e.g., Dorow et al. 2010). Therefore, some caution is encouraged before generalizing relationships between attitudes toward catch and general fishing behaviors.

A few apparent inconsistencies with prior propositions of specialization are worth noting that reduce the value of gear use as operationalized here as a metric of specialization. In fact, specialized gear use was positively associated with the least specialized Class 2. This result appears inconsistent with propositions by Bryan (1977) who associated the most specialized trout anglers with use of specific fly fishing gear. In our study, use of specialized gear may simply not reflect attributes related to participation that differentiated the three latent classes, suggesting that use of specialized gear may not covary with psychological commitment as measured by centrality to lifestyle. Almost no evidence existed for an association between other activity-specific metrics of specialization (e.g., harvest orientation, trophy orientation) and different fishing preferences here. Low reliability for this index, (i.e., Cronbach's $\alpha = .55$), however, suggests that these dimensions were not captured well in our survey, despite reliance on previously validated scales.

Support for the use of centrality to lifestyle for differentiating anglers of diverse preferences reflected differences among the latent classes in their willingness to pay to participate, as indicated by aversion to license cost and travel distance. Only minor differences among the three classes were found in preferences for catch expectations and harvest regulations. Therefore, dimensions of catch orientation did not predict class membership. Just as general constructs have limited ability to predict specific behaviors, so too are specific constructs when predicting general ones (Smith & Swinyard, 1983). Unlike other studies (e.g., Dorow et al., 2010; Fisher, 1997), little variance in preferences for management existed where others have found them to correlate with harvest orientation (at least among Minnesotan walleye anglers, Carlin et al., 2012). Our approach to include multiple species may have limited the ability of the choice model to capture preference variation among anglers for such specific attributes (Ditton et al., 1992; Fisher, 1997; Oh & Ditton, 2008). Certain regulatory preferences may only be relevant in a species-specific context (Dorow et al., 2010). As all catch-oriented attributes were tailored to each respondent's most frequently targeted species and presented as a range of levels reflecting species-specific catch distributions, variance associated with targeting a specific species was effectively neutralized and heterogeneity in our preference estimates was reduced to the extent that catch orientation co-varied with species preference. However, standardizing catch attributes also gave us a more generic model of angler behavior. Therefore, our method was ideal for evaluating the relationship of metrics of specialization and intended behavior for fishing in general. However, further research using species-specific case studies for evaluating relationships between activity-specific measures of specialization and fishing preferences is needed. Such context-specific research is also likely to be more relevant for management.

Angler preferences differed as expected regarding travel and license costs, with more specialized anglers indicating that they would travel farther or pay higher fees. However, some preferences that appear inconsistent with previous assertions were found. For example, specialized anglers are believed to suffer most from diminished resources (Oh & Ditton, 2008). Therefore, *ceteris paribus*, one would expect specialized anglers to strongly prefer opportunities offering healthy fish stocks. However, the influence of stock status on effort allocation was greatest for our least specialized (committed) Class 2 anglers. By contrast, Class 1 anglers, having greater centrality to lifestyle, and Class 3 anglers, who were the most travel-prone and species-specialized, were much less responsive to changes in stock status. Many behaviors of specialized anglers reflect the psychological dependency on fishing (Dorow et al., 2010; Salz & Loomis, 2005). For example, while casual anglers may limit effort to help stocks recover (Dorow et al., 2010), committed anglers may alter other behaviors (e.g., catch and release). Consequently, one should take care when referring to the "conservation behavior" (Oh & Ditton, 2008) of differently specialized anglers, as the types of behaviors and not just their magnitude may vary with specialization.

Given that this study was focused on one state in Germany, we caution readers about generalizing the findings too broadly. Although our study incorporated diverse fishing opportunities across ten species in both freshwater and marine systems, this diversity may be largely unique to the study area. Similarly, angler preferences may also reflect the particular institutional and cultural environment of northeastern Germany. Finally, there was some evidence of nonresponse bias toward more avid anglers (see Beardmore et al., 2011). Hence, the results likely do not accurately reflect the proportions of casual, intermediate, and advanced anglers in the entire population. Despite these limitations, the theoretical insights gleaned from the results have general value.

Conclusions and Implications

For a regional fishery with multiple species, angler behaviors of choosing fishing opportunities appears to be driven primarily by expenses (as expressed in license fees and travel costs), and specialization accounts for some variation in preferences for spatially segregated and diverse fishing opportunities. For general studies of fishing, researchers interested in a reasonably simple measure of specialization that efficiently explains diverse angler behavior may find centrality to lifestyle to be an adequate metric. Our results also underscored an important insight from social psychology—the explanatory power of constructs is related to matching the scale of the constructs (Smith & Swinyard, 1983). That is, general constructs (e.g., centrality to lifestyle) explain general behavioral intentions such as acceptability of costs and distance related preferences for site choices better than specific constructs (e.g., trophy fish orientation). That said, our research standardized all context dependent attributes, limiting heterogeneity observed in activity-specific attributes of the fishing opportunities. Therefore, other metrics of specialization may be better suited for studying anglers in specific fishing contexts. Further studies are warranted to develop suitable context-specific specialization metrics and examine their relationship with catch and regulatory preferences.

Accounting for diverse preferences and behaviors among anglers is a pressing research need not only for fisheries management but also in modeling the social-ecological dynamics of recreational fisheries at a regional scale (Hunt, Arlinghaus, Lester, & Kushneriuk, 2011; Hunt, Sutton, & Arlinghaus, 2013; Post, Persson, Parkinson, & Kooten, 2008). Enhancing the explanatory power and predictive capacity of choice experiments with behavioral concepts such as specialization may also enhance our understanding of ecological fishery dynamics through simulation models (Hunt et al., 2011; Johnston, Arlinghaus, & Dieckmann, 2010). For scientists, this approach can improve understanding fish and angler dynamics by incorporating multivariate preferences to predict angler behavior in such models (Johnston et al., 2010). For managers, this approach can reduce implementation uncertainty associated with regulatory change by predicting angler behavioral response more accurately (Hunt et al., 2013). Given the species-independent specification of our choice model, this approach may be useful for many regional fisheries where little or no information about angler behavior is known, with the limitation that our model reflects the cultural norms of behavior of Mecklenburg-Vorpommern anglers.

References

Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control*, *19*, 716–723.

Anderson, D. K., Ditton, R. B., & Hunt, K. M. (2007). Measuring angler attitudes toward catch-related aspects of fishing. *Human Dimensions of Wildlife*, *12*, 181–191.

Arlinghaus, R. (2007). Voluntary catch-and-release can generate conflict within the recreational angling community: A qualitative case study of specialized carp, *Cyprinus carpio*, angling in Germany. *Fisheries Management and Ecology*, *14*, 161–171.

Beardmore, B., Haider, W., Hunt, L. M., & Arlinghaus, R. (2011). The importance of trip context for determining primary angler motivations: Are more specialized anglers more catch-oriented than previously believed? *North American Journal of Fisheries Management*, *31*, 861–879.

Bryan, H. (1977). Leisure value systems and recreational specialization: The case of trout fishermen. *Journal of Leisure Research*, *9*, 174–187.

Buchanan, T. (1985). Commitment and leisure behavior: A theoretical perspective. *Leisure Sciences*, *7*, 401–420.

Burnham, K. P., & Anderson, D. R. (1998). *Model selection and inference: A practical information-theoretic approach.* New York, NY: Springer.

Carlin, C., Schroeder, S. A., & Fulton, D. C. (2012). Site choice among Minnesota walleye anglers: The influence of resource conditions, regulations and catch orientation on lake preference. *North American Journal of Fisheries Management*, *32*, 299–312.

Chipman, B. D., & Helfrich, L. A. (1988). Recreational specializations and motivations of Virginia river anglers. *North American Journal of Fisheries Management*, *8*, 390–398.

Ditton, R. B., Loomis, D. K., & Choi, S. (1992). Recreation specialization: Re-conceptualization from a social world perspective. *Journal of Leisure Research*, *24*, 33–51.

Ditton, R. B., & Sutton, S. G. (2004). Substitutability in recreational fishing. *Human Dimensions of Wildlife*, *9*, 87–102.

Donnelly, M. P., Vaske, J. J., & Graefe, A. (1986). Degree and range of recreation specialization: Toward a typology of boating related activities. *Journal of Leisure Research*, *18*, 81–95.

Dorow, M., & Arlinghaus, R. (2011). A telephone-diary-mail approach to survey recreational fisheries on large geographic scales, with a note on annual landings estimates by anglers in northern Germany. In T. D. Beard, R. Arlinghaus, & S. G. Sutton (Eds.), *The angler in the environment: Social, economic, biological and ethical dimensions* (pp. 319–344). Bethesda, MD: American Fisheries Society.

Dorow, M., Beardmore, B., Haider, W., & Arlinghaus, R. (2010). Winners and losers of conservation policies for European eel, *Anguilla anguilla*: An economic welfare analysis for differently specialized eel anglers. *Fisheries Management and Ecology*, *17*, 106–125.

Fisher, M. R. (1997). Segmentation of the angler population by catch preference, participation, and experience: A management-oriented application of recreation specialization. *North American Journal of Fisheries Management*, *17*, 1–10.

Graefe, A. R. (1980). *The relationship between level of participation and selected aspects of specialization in recreational fishing*. (Unpublished doctoral dissertation). Texas A&M University, College Station, TX.

Hunt, L. M., Arlinghaus, R., Lester, N., & Kushneriuk, R. (2011). The effects of regional angling effort, angler behavior, and harvesting efficiency on landscape patterns of overfishing. *Ecological Applications*, *21*, 2555–2575.

Hunt, L. M., Sutton, S.G., & Arlinghaus, R. (2013). Illustrating the critical role of human dimensions research for understanding and managing recreational fisheries within a social-ecological system framework. *Fisheries Management and Ecology*, *20*, 111–124.

Hurvich, C. M., & Tsai, C. L. (1989). Regression and time series model selection in small samples. *Biometrika*, *76*, 297–307.

Johnston, F. D., Arlinghaus, R., & Dieckmann, U. (2010). Diversity and complexity of angler behavior drive socially optimal input and output regulations in a bioeconomic recreational-fisheries model. *Canadian Journal of Fisheries and Aquatic Sciences*, *67*, 1507–1531.

Kerins, A. J., Scott, D., & Shafer, C. S. (2011). Evaluating the efficacy of a self-classification measure of recreation specialization in the context of ultimate frisbee. *Journal of Park and Recreation Administration*, *25*(3), 1–22.

Kim, S. S., Scott, D., & Crompton, J. L. (1997). An exploration of the relationships among social psychological involvement, behavioral involvement, commitment, and future intentions in the context of birdwatching. *Journal of Leisure Research*, *29*, 320–341.

Lancaster, K. J. (1966). A new approach to consumer theory. *Journal of Political Economy*, *74*, 132–157.
McFadden, D. (1974). The measurement of urban travel demand. *Journal of Public Economics*, *3*, 303–328.
McGurrin, J. (1988). Diversity in Gunpowder River trout anglers and implications for management. In A. G. Eversole, K. C. Sweeney, L. Smith, J. W. Foltz, S. Cooper, & D. E. Hammond (Eds.), *Proceedings of the fortieth annual conference* (pp. 111–116). Baltimore, MD: Southeastern Association of Fish and Wildlife Agencies.
Needham, M. D., Sprouse, L. J., & Grimm, K. E. (2009). Testing a self-classification measure of recreation specialization among anglers. *Human Dimensions of Wildlife*, *14*, 448–455.
Oh, C. O., & Ditton, R. B. (2006). Using recreation specialization to understand multi-attribute management preferences. *Leisure Sciences*, *28*, 369–384.
Oh, C. O., & Ditton, R. B. (2008). Using recreation specialization to understand conservation support. *Journal of Leisure Research*, *40*, 556–573.
Oh, C. O., Ditton, R. B., Anderson, D. K., Scott, D., & Stoll, J. R. (2005). Understanding differences in nonmarket valuation by angler specialization level. *Leisure Sciences*, *27*, 263–277.
Post, J., Persson, L., Parkinson, E., & Kooten, T. (2008). Angler numerical response across landscapes and the collapse of freshwater fisheries. *Ecological Applications*, *18*, 1038–1049.
Raktoe, B. L., Hedayat, A., & Federer, W. T. (1981). *Factorial designs*. New York, NY: Wiley.
Salz, R. J., & Loomis, D. K. (2005). Recreation specialization and anglers' attitudes towards restricted fishing areas. *Human Dimensions of Wildlife*, *10*, 187–199.
Scherer, K. R. (2005). What are emotions? And how can they be measured? *Social Science Information*, *44*, 695–729.
Scott, D., Ditton, R. B., Stoll, J. R., & Lee, T. (2005). Measuring specialization among birders: Utility of a self-classification measure. *Human Dimensions of Wildlife*, *10*, 53–74.
Scott, D., & Shafer, C. S. (2001). Recreational specialization: A critical look at the construct. *Journal of Leisure Research*, *33*, 319–343.
Smith, R. E., & Swinyard, W. R. (1983). Attitude-behavior consistency: The impact of product trial versus advertising. *Journal of Marketing Research*, *20*, 257–267.
Swait, J. (1994). A structural equation model of latent segmentation and product choice for cross-sectional revealed preference choice data. *Journal of Retailing and Consumer Services*, *1*, 77–89.
Vermunt, J. K., & Magidson, J. (2005). *Technical guide for Latent GOLD 4.0: Basic and advanced*. Belmont, MA: Statistical Innovations.