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Fishing for Understanding: A Mixed Logit Model of Freshwater Angler Preferences.

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Fishing for Understanding: A Mixed Logit Model of Freshwater Angler Preferences.

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Summary

Freshwater fisheries management requires knowledge of not only the resource but angler preferences and the extent to which preferences vary. This paper reports results from an internet-based stated preference survey of anglers in the North Canterbury region. Discrete choice models are used to investigate how the quality of fishery attributes impact anglers' selection of fishing sites. The models reveal significant preference heterogeneity between anglers for particular fishing site attributes. Furthermore, anglers' preference intensities for identical attributes vary between sites. Consequently, efficient allocation of resources entails spatial and social components.

Keywords: discrete choice analysis, latent class, mixed logit, angler heterogeneity, New Zealand recreational trout fisheries

Introduction

Freshwater recreational angling is a popular activity in New Zealand. Annual full-season license sales over the past decade have averaged 70,000 and the number of angler day trips per year is estimated to be approximately 1,000,000 (Unwin and Image 2003). A significant portion of this use is generated by overseas anglers whose expenditures on guides, accommodation, travel, etc. make New Zealand's freshwater fisheries significant tourism assets. New Zealand's South Island recreational trout fisheries, which are the focus of this paper, are renowned for pristine environments, high water visibility, large wild trout, low angler densities and relatively low cost of access (Hayes and Hill 2005). Given the South Island's varied climate, geology and topography a diverse range of trout fishing sites arises, offering qualitatively different experiences and requiring uniquely adapted angling techniques and equipment (Kent 2006).

Serious concerns have been raised by Fish and Game New Zealand (FGNZ), the body responsible for the maintenance, management and enhancement of the trout fishery resource, related to changing patterns of angler use of various types of fishing sites and license sale volatility (Abernathy 2006). Between the most recent National Angler Surveys (1994/1996 and 2000/2001) the North Canterbury Region has experienced some of the most drastic changes, with use of Lowland rivers and Mainstem rivers dropping 60% and 28% respectively. Concurrent use of the other predominant fishery types, Lakes and Backcountry rivers, increased only marginally over the same period (Unwin & Image 2003). Changes to use patterns and license sales volatility are serious threats to FGNZ, which relies solely on revenue from license sales to provide services to anglers. Further, redistributions of angling effort can lead to overfishing and unwanted resource pressure on fragile fisheries, particularly those in the backcountry (Walrond 2000; Young and Hayes 2004; White 2007).

It is not evident what is driving these changing activity patterns. Possible causes are environmental and site-attribute quality changes which are occurring at numerous New Zealand fishery sites. These changes are the result of influences such as, but not limited to, intensifying land uses (White 2007), *Didymosphenia Geminata* (Didymo) infestation (www.biosecurity.govt.nz/didymo) and angling pressure (Walrond 2000; Strickland and Hayes 2003; Strickland and Hayes 2004; Young and Hayes 2004). Complicating the matter is the fact that the types of change and degrees of change occurring to the individual Lowland rivers, Mainstem rivers, Backcountry rivers and Lakes are numerous and complex. Other influences on angler behaviour may include rising fuel prices, decreased time for recreation, changes in regulations, or angler congestion. Management strategies involve decisions over which fishing sites to manage, which attributes of those fishing sites to manipulate, (e.g. riparian margin erosion, or fish stocks), and which angler behaviours to control through fishery management regulations[1]. The myriad of factors which may impact anglers' behaviours highlights the difficulty for managers in developing management strategies, particularly if management resources are diminished because of decreased license sales.

Anglers are well known to exhibit diverse preferences and behaviours (Bryan 1977; Teirney and Richardson 1992; Train 1998). Angler heterogeneity adds complexity to management decisions because different anglers may prefer different regulations, environmental and fishing site attribute qualities. Further, because various fishing sites offer qualitatively different experiences and require uniquely adapted angling techniques and equipment, it is likely that angler preferences for similar attributes (e.g. catch rates or the absence of Didymo) on different fishing sites may vary. Improved understanding of the extent and nature of trout angler heterogeneity would allow New Zealand fishery managers to better allocate resources and to tailor management of fishery sites in ways that improve total angler satisfaction, maintain participation and redirect angling effort so that the natural environment is not overused.

Discrete Choice Analysis (DCA), which integrates random utility theory into a statistical model, has become a highly popular means for understanding angler preferences and forecasting angler choice; "the numerous applications (Train 1998) suggest that recreational fishing is the most popular outdoor recreation activity studied by choice modelers"(Hunt 2005). Recreational fishery managers can employ DCA to gain important insights into anglers' likely responses to new management scenarios. Though not the focus of this paper, DCA can be used to conduct

[1] "So what's motivating so many anglers to give trout fishing away? One obvious possibility is that they found their angling experience just didn't measure up to their expectations and this dissatisfaction was the catalyst for them dropping out. In this context, establishing what makes the difference between a good day's trout fishing and one that is not so good becomes critically important to understand how angling participation can be sustained. Although FGNZ can't do much to prevent a gusty north-westerly snarling up your cast, we can do something to prevent riverbeds becoming slick with algae due to pollution, and we can do something to facilitate access. If the root causes of angler dissatisfaction are factors we can influence, then we need to know what they are so we can remedy them" (Abernathy 2006 pg. 85).

nonmarket valuation and to estimate anglers' willingness-to-pay for fishing site improvements (Oh, Ditton et al. 2005). To improve understanding of angler preferences for various attributes and regulations on the different types of fishing sites, and the extent to which preferences vary among anglers, we estimate discrete choice models using anglers' stated choices collected in an internet-based choice experiment.

In the next section, we summarize the fundamental concepts of DCA, including the nature of stated choice experiments. We then report the study design process, including focus groups, experimental design generation, survey piloting, survey administration and results. The following section briefly describes survey participants and reports econometric results. The paper concludes with discussion and identifies some management implications.

Discrete choice analysis

DCA uses information on single preferred outcomes from a set of alternatives in order to make inferences about the relative values of attributes of those alternatives. The information used in DCA can come from observations of actual choices in a real setting (revealed preferences), or from choices made in hypothetical settings, known as choice experiments (stated preferences) (Louviere and Hensher 1982; Louviere and Woodworth 1983). Applied to anglers, the assumptions underlying DCA are as follows: individual anglers choose the alternative which provides the highest utility (Thurston 1927); individual anglers derive utility from of the constituent attributes of an alternative, not from the alternative itself (Lancaster 1966); from the analyst's perspective, an angler's utility is composed of two parts - an observable component and an unobservable component (Manski and Lerman 1977).

In applying DCA the analyst must observe attribute qualities associated with each alternative when the angler made their choice. The analyst specifies utility functions for each alternative in an individual angler's choice set. The utility function for each alternative is composed of a systematic part, which is the observed portion of utility, and a stochastic part, which is the unobserved portion of utility. The unobserved portion of utility arises because the analyst cannot accurately account for all attributes and factors which affect each individual's choice. While not fully accurate, the unobserved portion of utility can be likened to an error term. The analyst observes levels for the attributes present in the individuals' alternatives but cannot observe individuals' preferences. In order to estimate these preferences statistical procedures are used. Conventional choice models, such as the Multinomial Logit (MNL) model, use maximum likelihood estimation procedures to estimate parameters for each attribute in the observed portion of the utility function.

Let individual angler i's utility (U) for alternative j be composed of a vector of attributes X, describing the alternative and the individual. Vector β represents the angler's preferences. ε represents the unobserved portion of utility, with each individual's level of unobserved utility being random. Formally, U is defined as:

$$U_{ij} = \beta X_{ij} + \varepsilon_{ij} \qquad \text{where } \beta X_{ij} = V_{ij}$$

The probability of individual i selecting alternative n is

$$P_i(n) = \text{Prob}\,[V_{in} + \varepsilon_{in} \geq V_{im} + \varepsilon_{im}]\ \forall m \neq n$$
$$= \text{Prob}\,[V_{in} - V_{im} \geq \varepsilon_{im} - \varepsilon_{in}]\ \ \forall m \neq n$$

Different assumptions about the distribution of the unobserved effects ε gives rise to different choice model formulations. An assumption that the unobserved utility (ε_{ij}) for an angler's alternatives are independently and identically (IID) Extreme Value type 1 produces the MNL model (McFadden 1974; Train 2003) in which the probability that alternative n is chosen from all alternatives available to the individual is:

$$P(n) = \exp(\mu V_{in}).(\textstyle\sum_j \exp(\mu V_{ij})^{-1}$$

μ is a scale parameter, inversely proportional to the standard deviation of ε.

While it is the most commonly used choice model, MNL exhibits well known restrictions (Train 2003; Hensher, Rose et al. 2005). The first is that all anglers have homogeneous preferences. In other words, the parameter vector β is the same for everyone in the population. Secondly, because of the assumption that the unobserved utilities are distributed IID with extreme value distributions, the model assumes that individuals' repeated choices, whether in a SP or RP context, are uncorrelated. Thirdly, MNL exhibits the property known as Independence from Irrelevant Alternatives (IIA). IIA dictates that the ratio of choice probabilities for any pair of alternatives (in this case fishing sites) is independent of any other alternative available in the set of choices. The IIA property forces the assumption that anglers substitute to alternative fishing sites in a proportional manner. Consider, for instance, an angler's choice set which contains a lake, a backcountry river and a lowland stream. When IIA holds, a change in the attributes of one alternative, for instance closure of the lowland stream, would result in proportional changes in the probabilities of the angler selecting the lake and backcountry river alternatives. However, because of natural affinities for different locations and other reasons, such outcomes might not occur in practice.

Many DCA applications in recreational fisheries research (Bockstael, McConnell et al. 1989; Oh and Ditton 2006) have employed MNL and other restrictive choice model forms which conflict with the angler diversity identified in the leisure studies literature (Ditton, Loomis et al. 1992). MNL shortcomings are widely recognized in the choice modelling literature and a strong research emphasis over the past decade has been toward finding increasingly flexible models which accommodate individual heterogeneity and relax IID (Train 2003). DCA progression toward improved flexibility using logit formulations has included Nested Logit (NL) (Hauber and Parsons 2000), Cross Nested Logit (CNL) (Hunt, Boxall et al. 2007), and Latent Class models (LCM) (Boxall & Adamowicz 2002; Morey, Thatcher & Breffle 2006). However, these model forms are still semi-restrictive; for instance NL and CNL maintain preference homogeneity and IID within nests and LCM maintains IID and assumes preference homogeneity within latent classes.

The Mixed Logit (ML) model can overcome these limitations (Train 1998). ML allows preference parameters to be estimated over a parametric distribution which uncovers the extent of population heterogeneity. Further, ML allows correlation among an individual's choices and almost completely relaxes IID. Error components can be added to the ML to completely relax IID, allowing individuals' substitution patterns to become fully flexible.

The ML extends the MNL depiction of the utility function in the following manner:

$$U_{ij} = \beta X_{ij} + \eta X_{ij} + \varepsilon_{ij}$$

In this formulation β represents the population mean impact of attribute X on the angler's utility, while η is the population deviation relative to the population mean. As before, ε represents the unobserved portion of utility, which is IID and independent of other terms in the equation. Each individual's level of unobserved utility is random. The analyst observes X and estimates β and η. The analyst can test whether alternative parametric distributions for η, e.g., normal, lognormal, uniform or triangular, provide better approximations of population preferences. While not the focus of this paper, the ML model can be further specified to account for sources of heterogeneity in the distribution of random parameter means, variances and ε_{ij} using attributes of decision makers (Greene, Hensher et al. 2006; Greene and Hensher 2007).

The first study to introduce ML on the individual level investigated damages to recreational trout angling in Montana caused by mining operations (Train 1998). Train found statistically significant variation among angler preferences and for fishery attributes and also found that ML improved model statistical performance compared to MNL. Since Train's pioneering study ML has been widely applied in fields such as transport (e.g. Brownstone, Bunch & Train 2000), marketing (e.g. Revelt & Train 1998), and health economics (e.g. Borah 2006). However, there have been few further recreational angling applications. Phaneuf, Kling & Herriges (1998) found ML to significantly improve model performance when investigating individuals' site choices in the Wisconsin Great Lakes Region. Breffle, & Morey (2000) in their application to Maine and Eastern Canadian Atlantic salmon anglers found that ML explained choices significantly better then MNL and found that "restricting preferences to be homogeneous often leads to significantly different mean consumer surplus estimates" (Breffle & Morey 2000, p.2). Provencher & Bishop (2004) investigated the out-of-sample forecasting performance of MNL, LCM and ML in an application to salmon angling on Lake Michigan. They found that, while ML identified statistically significant preference heterogeneity among anglers and improved model fit relative to MNL, the ML model performed equally as well as LCM, and at least on one measure underperformed the MNL in terms of out-of sample forecasting.

One area overlooked by most, if not all, applications of DCA to recreational angling pertains to the estimation of site-specific preference parameters, rather than assuming that the same preference parameters apply to all sites. In other words, research has commonly assumed that the utility anglers derive from specific attributes is independent of the fishing site. Previous research (e.g. Train 1998) has relied on alternative specific constants to capture inter-site differences in anglers' behaviors. Our research calls into question this assumption, particularly in the case of New Zealand trout fisheries where diversity of fishing site settings, fishing site attributes and angler techniques abound. Further, relatively few studies have taken advantage of the benefits of stated preference data to estimate angler preferences using DCA. Hunt (2005) found that out of 50 studies in the published literature, only three of these used stated preference data (e.g. Banzhaf, Johnson & Mathews 2001). This study is the first DCA application to a New Zealand recreational trout fishery, it makes a novel contribution to the literature by estimating angler preferences for site-attributes at different fishing sites.

Survey Design

Revealed preference studies are problematic because of the large number of fishing sites (100+ in the North Canterbury region addressed in this study) and variable weather patterns in New Zealand freshwater fisheries. Some sites are unfishable in particular weather conditions, so weather variability makes collecting data on angler choices and measuring attributes of all fishing sites at the time when anglers made their decisions highly difficult. Consequently, a stated preference approach was adopted. Choice experiments have decided advantages for understanding New Zealand anglers' choices because they can overcome problems associated with multicollinearity and lack of variability in attribute levels found in actual fishing sites. They can also be used to restrict the number of choices and conditions at substitute sites. The initial step for designing the choice experiment was to decide which fishing site alternatives to use and which attributes to describe them with.

Focus groups and National Angler Survey categories identified the principle fishing site alternatives. These were: Mainstem-Braided River, Backcountry River, Lowland Stream, Lake, and Not Fish. Extensive literature reviews, consultation with FGNZ, and focus groups conducted with fishing clubs were used to ascertain salient fishing site choice attributes which were relevant to FGNZ management. The nine fishing site attributes chosen and the levels that the attributes could take are reported in Table 1.

Experimental designs are used to construct the arrangement of attribute levels shown to angler respondents for each alternative over different choice scenarios. Often the aim of experimental design generation is to vary the attribute levels in a way which maximizes understanding of angler preferences for the analyst. Use of prior information about angler preferences can greatly improve experimental design efficiency and minimizes the number of choice observations needed to achieve statistically significant model fits (Ferrini & Scarpa 2007; Rose & Bliemer 2005; Rose & Scarpa forthcoming). For this study a Bayesian D-Efficient design (Jaeger and Rose 2008) was generated based on information gathered in pilot studies undertaken using a hard copy survey of Nelson-Marlborough fishing club members and an internet survey administered to anglers in the Central South Island region. Feedback on the selection of attributes, attribute levels, alternative descriptions, ability to understand the survey, and choice complexity was also gathered during the pilots and used to refine the survey.

Portraying realism and importance to respondents in choice experiments is paramount (Cummings & Taylor 1998). Considerable care was taken to ensure that the attribute levels selected provided realistic choice scenarios. For instance, Backcountry Rivers generally have much higher water visibility, larger average trout size, and are more costly and time consuming to access than other fishing site types. Consequently, the study favoured alternative specific attribute levels which would reflect these differences (Table 1). Further, to maintain realism in the choice tasks, highly unrealistic attribute level combinations were not used; in particular scenarios with high cost accompanying low travel times. In addition, the attribute levels for Didymo and Riparian Margin were unbalanced. Ngene software was used to generate the Bayesian D-Efficient Design. The design resulted in 96 choice scenarios which were blocked into 16 randomised sets of six choice questions to eliminate order bias.

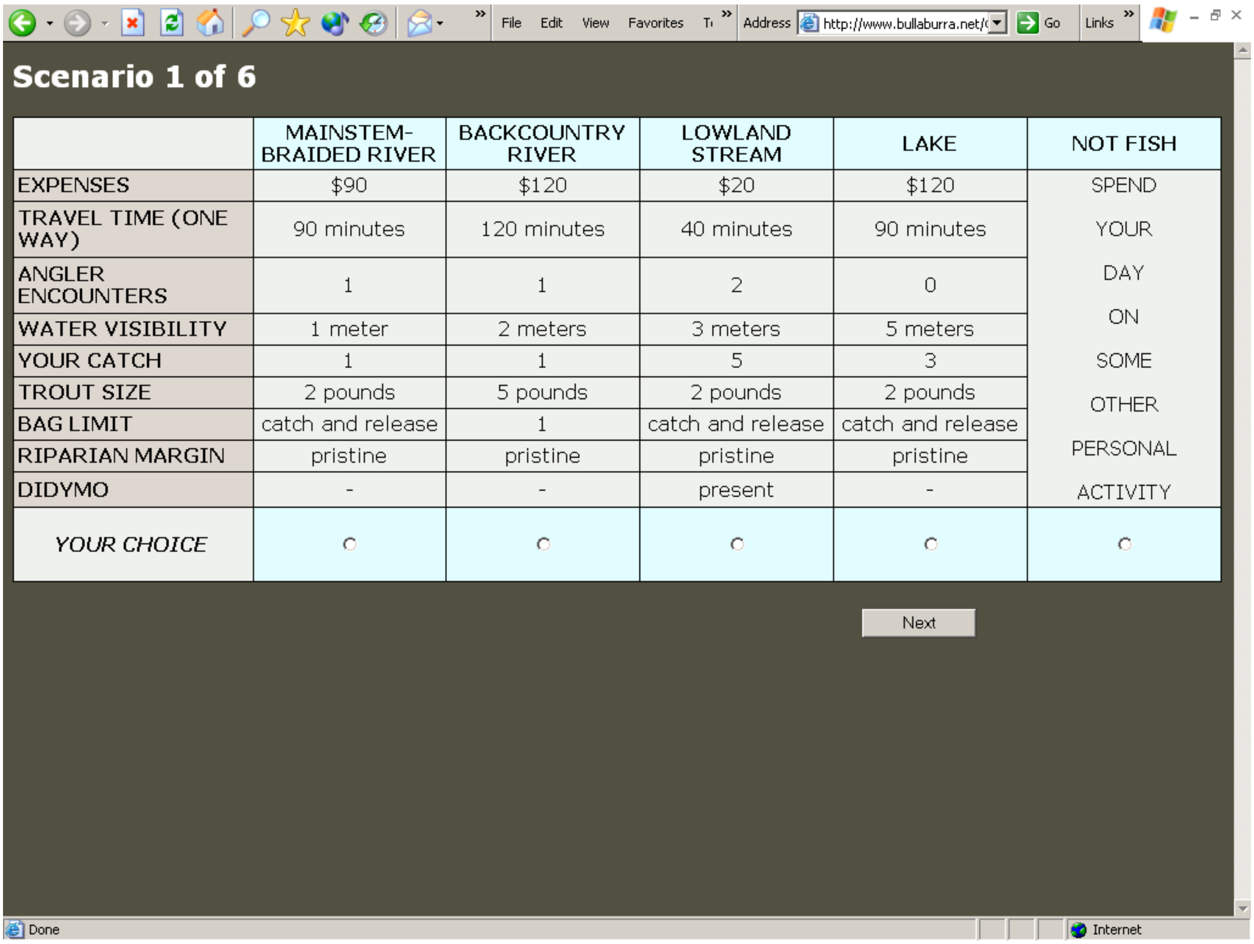
Table 1: Attributes

	Mainstem-Braided River	Backcountry River	Lowland Spring-fed Stream	Lake
Cost	\$30, \$60, \$90	\$60, \$90, \$120	\$20, \$40, \$60	\$60, \$90, \$120
One Way Travel Time (Minutes)	30,60,90	60,90,120	20,40 ,60	60,90,120
Angler Encounters	0,1,2	0,1,2	0,1,2	0,1,2
Water Visibility (Meters)	1,3,5	2,5,8	1,3,5	1,3,5
Angler Catch	1,3,5	1,3,5	1,3,5	1,3,5
Trout Size (lbs)	2, 3.5, 5	3.5, 5, 6.5	2, 3.5, 5	2, 3.5, 5
Bag Limit	0,2	0,1	0,2	0,2
Riparian Margin	Pristine, Erosion due to stock	Pristine, Erosion due to stock	Pristine, Erosion due to stock	Pristine, Erosion due to stock
Didymo	Present, Not Present	Present, Not Present	Present, Not Present	Present, Not Present

The sampling frame included the 6405 anglers with email contacts in the North Canterbury FGNZ database. An email from North Canterbury FGNZ invited survey participation. The message described the nature of the survey and its relevance and provided a web link to the survey. One reminder email notice was sent one week after the initial invitation. The survey ran for two weeks in April 2008.

The internet survey instrument consisted of multiple frames informing respondents of the nature of the choice experiment, along with directions and examples for completing the choice scenarios. The internet survey instrument was chosen over hard copy format due to advantages relating to cost and time savings (Dillman 2007). Considerable time was spent in the introduction to the survey describing the alternatives and their attributes and portraying the relevance of the survey to respondents (Cummings & Taylor 1998). In addition to completing six choice scenarios, each respondent was asked a number of questions relating to their angling background. The survey was designed to take 15 minutes. In order to motivate participation, respondents were entered into a draw to win their choice of a Sage fly rod or a \$1000 gift certificate to a New Zealand based fishing and hunting store. Figure 1 presents an example choice scenario screen.

Figure1: Choice scenario example



Scenario 1 of 6

	MAINSTEM-BRAIDED RIVER	BACKCOUNTRY RIVER	LOWLAND STREAM	LAKE	NOT FISH
EXPENSES	$90	$120	$20	$120	SPEND YOUR DAY ON SOME OTHER PERSONAL ACTIVITY
TRAVEL TIME (ONE WAY)	90 minutes	120 minutes	40 minutes	90 minutes	
ANGLER ENCOUNTERS	1	1	2	0	
WATER VISIBILITY	1 meter	2 meters	3 meters	5 meters	
YOUR CATCH	1	1	5	3	
TROUT SIZE	2 pounds	5 pounds	2 pounds	2 pounds	
BAG LIMIT	catch and release	1	catch and release	catch and release	
RIPARIAN MARGIN	pristine	pristine	pristine	pristine	
DIDYMO	-	-	present	-	
YOUR CHOICE	○	○	○	○	○

Next

Results

Usable responses were received from 813 of the 6405 people on the FGNZ database who were sent email invitations to complete the survey. These responses resulted in 4878 completed choice scenarios. Average survey completion time was 14 minutes and 57 seconds. It is not known how many of the emails that were sent were received by the intended recipients, so the actual response rate is unknown, but is greater than the 12.7% indicated by the figures above. The median respondent:

- Was between 41 and 50 years of age;
- Had 22 years of fishing experience;
- Fished 11-20 days per year;
- Earned $60,000 – $80,000 personal income;
- Fishing was their second most important recreational activity.
- Had intermediate fishing skill.

Only 8% of respondents were internationally based, with 84% living in Canterbury. Ninety five percent of participants were male, 19% belonged to fishing clubs, and 64% used the internet to access fishing-related information. Lakes were the most commonly fished waters, being fished by 76% of survey participants. Lakes were also the water type the anglers fished most often (26% of participants said they fished most often on Lakes). Corresponding figures for other water types were: Backcountry Rivers (73%, 23%), Braided Rivers (72%, 22%), Mainstem Rivers (65%, 19%), and Lowland streams (50%, 9%).

Nlogit 4.0 was used to conduct model estimation. Table 2 presents results from the multinomial logit model a two-class latent class model and a mixed logit model all estimated with non site-specific parameter estimates.

Table 2: Statistical Models (Generic Parameters)

	MNL (1)	LCM (2)		ML(3)	
		Class 1	Class 2	Mean	Spread (Triangular)
Cost	-0.00695***	-0.00772***	-0.00772***	-0.0150***	0.0377***
Travel Time	-0.00567***	-0.00388*	-0.00779***	-0.00825***	0.0309***
Visibility	0.0518***	0.0926***	0.0315***	0.0697***	0.375***
Catch	0.110***	0.156***	0.0938***	0.142***	0.655***
Fish Size	0.166***	0.262***	0.143***	0.226***	0.692***
Bag	0.187***	-0.00000	0.269***	0.207***	1.170***
Margin	-0.418***	-0.586***	-0.392***	-0.575***	1.269***
Didymo	-0.284***	-0.357***	-0.283***	-0.407***	1.413***
Encounters	-0.038	-0.273***	0.0605***	-0.0836***	0.602***
Mainstem	0.140	-0.0576	0.318	1.012***	
Backcountry	0.590*	1.303**	0.105	1.434***	
Lowland	-0.157	-0.399	-0.0202	0.554**	
Lake	0.122	-0.0151	0.326	0.951***	
Constant		-1.326***	0		
Fly only		1.008***	0		
All methods		-2.627**	0		
Backcountry		2.008***	0		
Beginner		-1.172***	0		
Class Prob		0.336	0.664		
Parameters	13	30		22	
AIC	2.935	2.813		2.753	
BIC	2.952	2.853		2.782	
LL	-7144.692	-6831.230		-6692.311	

Note: ***, **, * = Significance at 1%, 5%, 10% level

The use of maximum likelihood estimation and not ordinary least squares as the estimation procedure necessitates use of statistical tests other than the *F*-statistic to determine how well the parameters fit the data. The Akaike and Bayesian Information Criteria (AIC and BIC), are two measures which can used to compare models with different numbers of parameters. Lower scores are preferred. The likelihood ratio test (LRT) may also be used to compare models.

Parameter estimates in the MNL (1) carry expected signs. Higher cost and greater travel time were both evaluated negatively, as were damaged riparian margins and didymo infestations. Increased encounters with others were not significant. Better water visibility was evaluated positively, catching more trout, bigger trout and increased bag limits were all evaluated positively. The alternative specific constants indicate the mean effect of all unobserved influences on anglers' choice for each fishing site alternative. The positive and significant alternative specific coefficient for Backcountry River indicates that, *ceteris paribus*, anglers preferred to fish at a Backcountry River.

The LCM (2) reported in Table 2 incorporates a limited degree of angler heterogeneity. The two-class model is presented here for brevity; three and more-class models allow further discrimination. The two-class model is preferred over the MNL (1) on AIC, BIC and likelihood ratio test criteria ($\chi 2 = 626.9$, 17 degrees of freedom, $p<0.000000$) and reveals significant preference heterogeneity not uncovered by MNL (1). Preferred fishing method, preferred fishery type and experience were important determinants of class allocation. The positive coefficient for fly only shows that anglers who fish exclusively with fly were more likely than others to be a member of Class one. Class one anglers were not influenced in their choice of sites by bag limits, whereas bag limits were strong positive influences for Class two anglers. Class one anglers' site choices were negatively influenced by encounters, whereas class two anglers preferred encounters with other anglers. Class one anglers preferred Backcountry Rivers, *ceteris paribus*.

The mixed logit model was estimated using triangular distributions. Constraints on spread parameters, (and hence on heterogeneity), while offering behaviorally sensible outcomes because they restrict the signs on parameters, resulted in poorer model fit. Spread parameters in Table 2 are unconstrained. Shuffled Halton draws were specified in preference to regular Halton draws because they provide better coverage of the distribution space when estimating a large number of parameters (Bhat 2003; Train 2003, pg 236). Model convergence and parameter stability occurred when 2500 draws were used. Based on AIC, BIC and likelihood ratio test criteria ML (3) offers an improvement in fit over both MNL (1) and LCM (2). All spread parameters were highly significant, indicating the presence of heterogeneity. All mean parameters have expected signs and are significant. All alternative specific constants are significant.

In order to test the hypothesis that site-specific parameters better capture angler preferences multinomial logit, latent class and mixed logit models were estimated with site specific parameters (Table 3). Cost and travel time parameters were specified to be invariant across fishing sites. Adoption of site-specific parameters for the remaining attributes added computational burden but permitted investigation of whether anglers' taste intensities for similar attributes differed across the various fishing site types.

The site-specific MNL (4) model has the same overall pattern as the generic MNL (1) model, with two notable differences. No site-specific constants were significant in the expanded model, whereas the constant for Backcountry Rivers was positive, although of marginal significance, in the generic model. Whereas encounters were not significant in the generic model, they had a low level of significance in the backcountry in the site-specific model. The role of encounters is highlighted more clearly by the site specific LCM (5). Encounters were negative influences on Class one anglers' choice of Mainstem-Braided, Backcountry and Lowland Rivers.

Encounters acted as positive influences on Class two anglers' probability of choosing to fish Backcountry Rivers. Encounters were not significant influences on choice of Lakes for either class. Better water visibility was a positive determinant of choice on Mainstem and Backcountry Rivers and on Lakes for Class one anglers, but was unimportant for Lowland streams or for Class two anglers at Lakes. Models that incorporate site-specific attribute parameters contrast the differential importance of visibility at different fishing sites.

The site specific ML (6) model was estimated using triangular distributions, which performed best on statistical grounds. Like the generic ML model specification, constraints placed on the spread parameters resulted in a poorer model fit. Spread parameters in Table 3 are unconstrained. Shuffled Halton draws were specified. Parameter stability was achieved with 1500 draws.

ML (6) spread parameters for water visibility on Mainstem Rivers and for catch on Lakes were non-significant, indicating that angler preferences were homogeneous for these particular site attributes. The mean parameter estimate for water visibility on Lowland Streams was not significant, in contrast to MNL (4), but consistent with LCM (5). Parameter means for encounters on all fishing sites were insignificant. All other attribute spread and mean parameters were significant. The large numbers of significant spread parameters were again indicative of preference heterogeneity amongst anglers.

Table 3: Statistical Models (Alternative Specific Parameters)

	MNL (4)	LCM (5)		Mixed Logit (6)	
		Class 1	Class 2	Mean	Spread
Cost	-0.00623***	-0.00697***	-0.00697***	-0.00917***	0.0413***
Travel Time	-0.00497***	-0.00293	-0.00734***	-0.00779***	0.0276***
Visibility: Main	0.0817***	0.123**	0.0792***	0.124***	0.183
Visibility: Back	0.0730***	0.0963***	0.0637***	0.083***	0.451***
Visibility: Low	0.0495**	0.104	0.0281	0.0426	0.411***
Visibility: Lake	0.0462*	0.167***	-0.00575	0.074*	0.424***
Catch: Main	0.121***	0.153**	0.118***	0.122***	0.546***
Catch: Back	0.189***	0.229***	0.204***	0.256***	0.598***
Catch: Low	0.119***	0.148**	0.113***	0.103***	0.492***
Catch: Lake	0.0781***	0.159***	0.0453**	0.136***	0.265
Fish Size: Mai	0.239***	0.367***	0.213***	0.304***	0.361***
Fish Size: Back	0.268***	0.311***	0.373***	0.424***	0.541***
Fish Size: Low	0.144***	0.161*	0.149***	0.138***	0.452***
Fish Size: Lake	0.116***	0.239***	0.0580*	0.163***	0.709***
Bag: Main	0.201***	0.00616	0.278***	0.332***	1.321***
Bag: Back	0.125***	-0.0254	0.365***	0.232***	1.540***
Bag: Low	0.1394***	-0.00718	0.188***	0.221***	1.264***
Bag: Lake	0.1728***	-0.0720	0.270***	0.273***	0.806*
Margin: Main	-0.484***	-0.817***	-0.414***	-0.662***	1.0406***
Margin: Back	-0.497***	-0.701***	-0.503***	-0.788***	1.844***
Margin: Lowl	-0.447***	-0.556***	-0.449***	-0.626***	0.754**
Margin: Lake	-0.358***	-0.333***	-0.373***	-0.595***	2.081***
Didymo: Main	-0.376***	-0.432***	-0.382***	-0.487***	1.639***
Didymo: Back	-0.376***	-0.490***	-0.408***	-0.524***	1.812***
Didymo: Low	-0.255***	-0.169	-0.310***	-0.349***	1.406***
Didymo: Lake	-0.245***	-0.280**	-0.228***	-0.399***	1.727***
Encounters: Main	-0.0571	-0.350***	0.0189	-0.0726	0.558
Encounters: Back	-0.0695*	-0.303***	0.155***	-0.0204	0.443
Encounters: Low	-0.0389	-0.324***	0.0418	-0.0851	0.628
Encounters: Lake	0.00550	-0.123	0.0477	0.0285	0.660*
ASC: Main	-0.174	-0.724	0.0489	-0.00512	
ASC: Back	-0.324	0.624	-1.768***	-0.920	
ASC: Low	0.0513	0.0295	0.141	0.529	
ASC: Lake	0.507	-0.263	1.113***	0.309	
Constant		-1.234***	0		
Fly only		0.996***	0		
All methods		-2.256**	0		
Backcountry		1.933***	0		
Beginner		-1.170***	0		
Class probs		0.348	0.652		
Parameters	34	72		64	
AIC	2.937	2.815		2.744	
BIC	2.982	2.911		2.829	
Log likelihood	-7128.411	-6794.241		-6628.056	

Note: ***, **, * = Significance at 1%, 5%, 10% level

Table 4 summarizes statistical fit measures for the models in Tables 2 and 3.

Table 4: Model fit

	Form	Site-specific	LL	Parameters	AIC	BIC	Likelihood Ratio Test (Specific vs Generic)
1	MNL	No	-7144.7	13	2.935	2.952	
2	LCM	No	-6831.2	30	2.813	2.853	
3	ML	No	-6692.3	22	2.753	2.782	
4	MNL	Yes	-7128.4	34	2.937	2.982	32.6, 21, 0.0508
5	LCM	Yes	-6794.2	72	2.815	2.911	74.0, 42, 0.0017
6	ML	Yes	-6628.1	64	2.744	2.829	128.4, 42, 0.0000

Likelihood Ratio Test : χ^2, degrees of freedom, p

Generic versus Site-Specific Parameters

Comparisons between models 1 & 4, 2 & 5, and 3 & 6 test the significance of site-specific parameters (Table 4). Evidence is mixed. AIC and BIC scores increased with the site-specific attribute models for the MNL and LC models - although the difference was small. For the ML model there was a decrease in AIC in moving to the site-specific model, although BIC increased. These results indicate that the more parsimonious generic models are preferred. In contrast the LRT tests suggest the site-specific models are preferred.

Angler heterogeneity

Test of the importance of heterogeneity are provided by comparisons of multinomial logit models, which do not permit angler heterogeneity, with latent class and mixed logit models, which do accommodate heterogeneity (Table 4). For all cases the heterogeneous models, despite additional parameters, significantly improve behavioural predictions, as evidenced by the decreasing AIC and BIC scores. ML, which allows for individual preferences, outperforms LCM, which imposes within-class homogeneity, based on the AIC, BIC and likelihood ratio test criteria.

Discussion & Management implications

The application of discrete choice analysis to a New Zealand freshwater fishery has been the result of a long period of investigation of anglers' motivations and expectations. The close working relationship developed with anglers during the design of the study was critical to enabling development of a stated preference study design that was realistic to anglers, could be applied over the internet, provided sufficient motivation for anglers to participate, and allowed revelation of their underlying preferences. Modelling the complex decisions regularly faced by anglers, with large numbers of alternatives and many salient attributes that vary across sites, is a complex statistical task requiring a large amount of data. Internet application, while incurring substantial setup costs, allowed a large amount of data to be collected relatively quickly and cheaply.

An important component of this research is prediction of changes in resource use contingent upon environmental changes. For example, what angler pressures would arise in other fisheries if didymo were to result in closure of backcountry fisheries? Anglers use many types of sites, with at least two thirds of anglers using each water type except Lowland streams. This indicates a flexible population, likely to be willing to transfer activity between locations according to conditions. The strength of the model parameters estimated so far indicates that anglers are indeed willing to transfer their fishing effort to alternative sites, although some anglers have strong preferences for particular waters. The implication is that loss of some waters has the potential to dramatically increase angler pressure on other waters.

These results arise from initial investigations of a rich data set. However, even at this early stage the role of respondent heterogeneity is apparent. Both the latent class model and the mixed logit model indicate that there are distinct differences in tastes between anglers. These taste heterogeneities are consistent with other recent discrete choice recreation studies (Train 1998; Breffle & Morey 2000). While the mixed logit models indicated the wide reaching extent of preference heterogeneity among New Zealand anglers, they did not, in this instance, provide any indication of the location of specific angler subtypes or individuals on the parameter distributions in order to identify the characteristics of individuals with specific taste intensities. The latent class models in this instance enriched the understanding of angler heterogeneity by beginning to tease out distinct preferences among subgroups, and possible sources of heterogeneity. For instance, the parsimonious latent class model which was used to estimate generic parameters uncovered two classes of anglers with disparate preferences for angler encounters.

Bryan (1977) hypothesised that as anglers become more specialised they refine their choice of equipment and become more sensitive to resource disturbance and encounters with others. Concern shifts from simply catching fish to catching larger fish, in pristine environmental settings with minimal management influence, using specialised equipment and skills. Bryan's (1977) hypotheses are consistent with the simple latent class models presented here. Members of Class one fit the mould of highly specialised anglers - what Bryan termed technique specialists and technique-setting specialists; these anglers are more likely to be highly skilled, favour Backcountry Rivers, are less likely to be technique generalists and beginners, are averse to encounters with others, and are not concerned with bag limits. The relatively larger parameters on fish size, didymo and riparian margin estimated here for Class one anglers are consistent with Bryan's conjecture that specialised anglers have strong preferences for larger size, and are more negatively affected by environmental degradation. Class two anglers are consistent with what Bryan termed occasional or generalist anglers. The contrast between the two latent classes emphasises the need for fisheries managers to understand and account for angler heterogeneity in managing freshwater fisheries.

The adoption of site-specific parameters was expected to add explanatory power. However, the statistical measures used to compare model fit were inconclusive. Based on AIC and BIC criteria, the expected improvements of site specific models over the generic models did not occur. However, likelihood ratio tests indicated some improvement. Regardless of these conflicting performance-based statistical tests, the site-specific models offer some important insights and will be the subject of further investigation. For example, water visibility clearly has a different role at alternative sites. Fishing methods used in Lakes and Lowland streams are not dependent on sight fishing – consequently the non-significance of these parameters is understandable. Similarly, the role of encounters varies. Encountering other anglers on a Backcountry River, which is likely to have disturbed the fish, is quite different to encountering others while fishing on a lake where the fish are more dispersed and anglers and fish are not visible to each other.

Some attributes seem to have similar effects at different sites. Examples are margin and didymo, particularly in the MNL model. The coefficients across sites are remarkably uniform. The small differences in magnitude, while possibly statistically significant, probably add little to the predictive ability of the model. Further investigation of which attribute parameters differ across sites has the potential to improve model performance.

The next challenge for analysis of this data set is provide additional enrichment to the understanding of the nature of heterogeneity, particularly to identify which sectors of the angler community hold different types of preferences and to further extend ML with error components to capture differing variances in the unobserved effects. The later enhancement will permit a richer understanding of anglers' substitution patterns.

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