Fishing for more understanding: a mixed logit-error component model of freshwater angler site choice

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Summary

Recreational anglers are known to seek different types of experiences in different settings. Such preference and behavioural diversity has important management implications. Research methods which assume only a limited degree of preference heterogeneity and impose rigid substitution patterns can impair understanding of individual's unique decision process and lead to misguided management and policy recommendations. This paper reports results from an internet-based stated preference survey of recreational trout anglers in the North Canterbury Region of New Zealand. A mixed logit model, which simultaneously specifies random parameters plus error components, is used to capture the extent of random preference heterogeneity in systematic utility along with variance differences in unobserved utility at the alternative specific level. These error components are independent of the random parameters and fully relax the IID property. The model is further generalised to control for heterogeneity in the means and heteroscedasticity in the variances of the random parameters as well as error components using angler's self reported skill level. The performance of the extended mixed logit-error component specification is evaluated against multinomial logit and latent class.

Keywords: random utility model, latent class, mixed logit, error component, heterogeneity, recreational angler

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 days per year is estimated to be approximately 1,000,000 (Unwin & 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, large wild trout, low angler densities and relatively low cost of access (Hayes & Hill, 2005).

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Given the South Island's varied climate, geology and topography a diverse range of trout fishing sites arise. The predominant range of sites can be categorised as Mainstem rivers, Backcountry rivers, Lowland rivers and Lakes (Unwin & Image, 2003).

The fishing site types available to anglers generally feature different scenic qualities and offer qualitatively different angling experiences, which require uniquely adapted angling techniques and equipment (Hayes & Hill 2005; Kent 2006). For instance Backcountry rivers often have highly scenic qualities, high water visibility and "spooky" trout. Here, anglers are known to wear polarized sunglasses to "stalk" trout before casting, use lightweight graphite fly rods, tiny imitations representative of insects, and extremely long, fine, tapered leaders. On Mainstem rivers, which have relatively lower water visibility particularly in their lower reaches, trout cannot often be sighted and anglers employ "blind casting" tactics with heavy-duty fly or casting rods, short stout leaders and heavily weighted flies and lines. Multiple types of techniques are employed on Lowland streams including both of those used on Backcountry and Mainstem-braided rivers. Techniques and equipment used by fishers on lakes often involve personal watercraft, downriggers and fish-finding sonar, which are distinctly different then those employed on river sites (Kent 2006).

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. The first concern relates to changing patterns of angler use of various types of fishing sites. The problem is most pronounced in the North Canterbury Region where use of Lowland rivers and Mainstem rivers declined by 60% and 28% respectively and use of Backcountry rivers increased by approximately 18% according to the two most recent National Angler Surveys 1994/1996 and 2000/2001 (Unwin & Image 2003). In the same period use of North Canterbury Lakes increased only marginally.[1] Redistributions in angling effort, such as this, can be problematic for fishery managers as it can lead to overfishing and unwanted resource pressure on fragile fisheries, particularly those in the backcountry (Walrond, 2000; White 2007; Young & Hayes, 2004). In recent years measures have been taken by FGNZ to limit congestion on some backcountry rivers outside of North Canterbury, such as the Greenstone, Caples and Oreti in the Otago and Southland regions, respectively. The second concern of FGNZ relates to license sales, which, in the North Canterbury region have steadily declined over the past two decades with some year to year fluctuations bucking the trend. Declining license sales is problematic for managers as it reduces their revenue and ability to maintain the fisheries, as well as provide services to anglers (Abernathy, 2006).

It is not clear what is driving the redistributions in angling use of fishery site types and decreasing participation in the North Canterbury Region. Possible causes may be due to fishing site environmental disturbances. Some of these disturbances have been the result of intensive land use practices by the agricultural sector and the shift toward dairying (White 2007). It is well documented that agricultural practices have resulted in erosion to lake and stream riparian margins, loss of water quality and loss of trout stocks (Hayes 2002). Holland (2006 p.98) highlights the magnitude and rapidity of this degradation, "…73% of [North Canterbury] spring-fed lowland streams in 2005 [are] in poor ecological health –up from 27% in 1999". Other environmental changes to fishing sites include *Didymosphenia geminata* (Didymo) infestation. Didymo was first detected in 2004 and is now established in approximately 70 river and lake sites on the South Island (www.biosecurity.govt.nz/didymo). There is also evidence that trout are less catch-able, particularly in remote backcountry rivers,

[1] The 2007/2009 National Angler is currently in process.

due to increasing angler pressure (Strickland & Hayes, 2003; Strickland & Hayes, 2004; Walrond, 2000; Young & Hayes, 2004).

The types of attribute quality change and degrees of change are variable across individual Lowland rivers, Mainstem rivers, Backcountry rivers and Lakes. For instance, and in general, Lowland rivers have been subject to more acute riparian margin erosion, loss of fish stock and degraded water quality compared to Backcountry Rivers and Lakes due to their proximity to intensive agricultural development. On the otherhand Lowland rivers appear to be less susceptible to reduced trout catch-ability (Young and Hayes 2004), and Didymo infestation compared to Backcountry rivers. The factors underlying recent changes in angler activity may not just be confined to environmental issues. Other possible influences on angler activity may include constraints such as rising fuel prices, decreased time for recreation, changes in regulations, or localised angler congestion (Strickland & Hayes, 2003; Strickland & Hayes, 2004; Walrond, 2000; Young & Hayes, 2004).

Identifying the degree to which fishing site attribute quality changes are influencing angler behaviour is complicated because it is well known that anglers seek different types of experiences in different settings (Bryan 1977; Teirney and Richardson 1992; Train 1998). Such preference and behavioural diversity adds complexity to the problem of understanding how fishing site attributes (and changes in the quality thereof) influence angler decisions of whether and where to fish. For instance, different anglers may prefer different regulations, environmental and fishing site attribute qualities with preference intensities differing between alternative fishing site types. Further some fishing site types may act as closer substitutes compared to others and thus angler substitution patterns may be non-proportional. For example, change (e.g., degradation) or closure to an individual fishing site type (e.g., Lowland river) may cause anglers to redistribute predominantly to one particular fishing site type (e.g., Backcountry river) instead of evenly to all other alternatives (Mainstem rivers, Backcountry rivers, Lakes). If a satisfactory substitute is not available, some anglers may opt to not fish. The National Angler Survey findings along with longitudinal license sale figures suggest a complex story of preference heterogeneity, non-proportional substitution patterns and participation opt-out among New Zealand anglers. In this paper, we set out to understand North Canterbury angler's preferences for fishing site attribute qualities, the extent to which preferences vary and substitution patterns to help inform management decisions.[2]

Random Utility Models (RUMs), which integrate random utility theory (Thurstone 1927; Luce 1959, Marschak 1960) into a statistical model, have become highly popular means for understanding the determinants of, 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 use RUMs to gain important insights into anglers' likely responses to new management scenarios or environmental disturbances. Though not the focus of this paper, RUMs can be used to conduct nonmarket valuation and to estimate angler's willingness-to-pay for fishing site improvements (e.g., Oh, Ditton, Anderson, Scott, & Stoll, 2005). To improve understanding

[2] "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).

of the influence of various attributes and regulations on New Zealand recreational trout angler site choice, the extent to which preferences vary among anglers, and angler substitution patterns, we explore advanced RUMs, namely mixed logit which simultaneously allows for the revelation of random preference heterogeneity and actual substitution patterns, using anglers' stated choices collected in an internet-based choice experiment. We compare the statistical fit, predictive performance and information revelation of these mixed logit models with multinomial logit and latent class RUMs.

In the next section, we summarize the fundamental concepts of RUMs. Next we describe and specify the multinomial Logit, latent class and mixed logit models, 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 models are then used to forecast anglers' likely responses to a scenario involving environmental disturbance to riparian margins, water visibility and catch rates on Lowland fishing sites. Forecasts from the different models are compared. The paper concludes with discussion and identifies some management implications.

Random Utility modelling

In the context of individual choice RUMs use information on a single preferred decision outcome from a set of alternatives in order to make inferences about the relative influence of attributes of those alternatives. The choice information used in RUMs 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 & Hensher, 1982; Louviere & Woodworth, 1983). Applied to anglers, the assumptions underlying RUMs are as follows: individual anglers choose the alternative which provides the highest utility (Thurston, 1927); utility is comprised of constituent attributes of an alternative (Lancaster 1966); from the analyst's perspective, angler's utility is composed of two parts - an observable component and an unobservable component (Manski & Lerman, 1977).

In applying RUMs the analyst must observe attribute qualities (levels) associated with each alternative when the angler made their choice. Utility functions are specified for each alternative in anglers' choice sets. 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 systematically account for all influences on each individual's choice, because these influences may be idiosyncratic or be related to influences which data are difficult to attain. An assumption must be made as to what the distribution of these unobserved effects (unobserved utilities) are for the population. This assumption is a critical one as different assumptions give rise to different choice model forms. The analyst observes levels for the attributes present in each individual's alternatives but cannot observe the individual's 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.

The utility U to individual angler $i=1,\ldots,$N for an alternative J is a function of a vector of attributes x describing the alternative and individual. Vector β represents the anglers preferences (marginal utilities) which the analyst wishes to estimate.[3] In this specification the vector β is not individual-specific. ε represents the unobserved portion of utility (plus measurement error, plus estimation error) with each i's level of unobserved utility being random, with α_j, the alternative specific constant (asc) measuring the mean effect of unobserved utility for alternatives. J-1 ascs may be estimated. Formally, let i's utility for alternative j be defined as:

$$U_{ij} = \alpha_j + \beta x_{ij} + \varepsilon_{ij} \tag{1}$$

Suppressing α_j for the moment, the probability of individual i selecting alternative j is:

$$P_{ij} = Prob\ [U_{ij} > U_{iq}] \qquad \forall q \neq j$$

$$P_{ij} = Prob\ [\beta x_{ij} + \varepsilon_{ij} > \beta x_{iq} + \varepsilon_{iq}] \qquad \forall q \neq j$$

$$P_{ij} = Prob\ [\beta x_{ij} - \beta x_{i} > \varepsilon_{iq} - \varepsilon_{ij}] \qquad \forall q \neq j$$

Different assumptions about the distribution of the unobserved effects ε give rise to different choice model formulations. An assumption that unobserved utilities (ε_{ij}) are independently and identically distributed (IID) Extreme Value (EV) type 1 produces the MNL model (McFadden, 1974; Train, 2003) in which the probability that the choice outcome (y_i) is alternative j from all alternatives available to the individual is:

$$P(y_i = j) = \frac{\exp\mu(\beta \mathrm{x}_{ij})}{\sum_{q=1}^{J} \exp\mu(\beta \mathrm{x}_{iq})} \tag{2}$$

μ is a scale parameter which is inversely proportional to the standard deviation of ε. For MNL μ is assumed to equal 1.

While MNL is the most commonly used choice model, MNL exhibits well known restrictions which limit realism and information revelation, particularly in cases where individuals have diverse preferences and behavioural expressions (Hensher, Rose, & Greene, 2005; Train, 2003). First, with MNL all anglers are assumed to exhibit random preference heterogeneity of degree zero - vector β is an estimate of population means as in (2).[4] Second, MNL assumes that individuals' unobserved utility, whether in a SP or RP context, is uncorrelated across alternatives and over repeated choices. In other words factors in unobserved utility are assumed to be totally random. Briefly, consider individuals' choices which are influenced by fishing site scenic quality and that scenic quality is not specified in systematic utility for any alternative (for whatever reason - perhaps data are difficult to measure and attain). By not formally specifying scenic quality in systematic utility, the influence is forced into unobserved utility, ε_j. If utility for scenic quality is resident in unobserved utility (and a salient determinant of choice) across choice situations then correlation is induced in ε_j's,

[3] Note: In this instance βs are also referred to in the literature as preference parameters, estimated coefficients and marginal utilities.

[4] Heterogeneity can be introduced into the systematic portion of utility by interacting (multiplying or dividing) individuals' characteristics with attributes. This procedure does not however permit random heterogeneity.

violating IID. Third, MNL exhibits the property known as Independence from Irrelevant Alternatives (IIA) because of the assumption that unobserved utility is distributed IID EV type1. 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 Mainstem river, a Backcountry river, a Lowland river and a Lake. 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 Mainstem river, Backcountry river and Lake alternatives. However, because of natural affinities for different locations or constraints, such outcomes might not occur in practice. For instance, personal watercraft are often necessary for angling on lakes. For those anglers affected by the Lowland river closure and without personal watercraft it would seem more likely that these anglers would substitute to a river-based alternative or not fish at all. MNL imposes substitution patterns rather then letting substitution patterns be revealed by the data. We now discuss RUM specifications which offer more flexibility than MNL in terms of accommodating random heterogeneity and identifying realistic substitution patterns.

MNL shortcomings are widely recognized in the choice modelling literature and a strong research emphasis has focused on developing increasingly flexible models which relax the restrictive properties of MNL (Train 2003). These developments include generalised extreme value (GEV) models which include nested logit, cross nested logit and heteroscedastic extreme value models through the nesting of alternative's error structures. Briefly, all GEV models, like MNL, assume random preference heterogeneity of degree zero in systematic utility and are only able to partially relax the IID assumption of MNL. Since there is reason to believe that New Zealand trout anglers exhibit both random preference heterogeneity and non-proportional substitution patterns we move on toward more recent developments in RUMs which have the capacity to handle both aspects. The majority of recreational fisheries research employing RUMs have employed MNL (Bockstael, McConnell, & Strand, 1989; Oh & Ditton, 2006) or semi restrictive GEV models (e.g., Morey, Rowe & Watson 1993; Hauber & Parsons, 2000; Hunt, Boxall and Boots 2007)

Latent class models (Swait 1994) are a more recent development and can capture unobserved preference heterogeneity through a simultaneous estimation process that employs joint probability of whether a particular angler chooses a fishing site and the probability of an angler belonging to a class of individuals which share identical characteristics and preferences. Within classes, choice probabilities are estimated in a manner analogous to MNL. Individuals' class membership is not observed. A number of recreation-based studies have employed the latent class RUM (e.g., Boxall & Adamowicz 2002; Scarpa & Theine 2005; Morey, Thatcher & Breffle 2006; Scarpa, Thiene & Tempesta 2007; Hynes, Hanley & Scarpa 2008).

Following Greene (2007), consider a situation where an individual *i* resides in a 'latent class' *C*. Individual *i*'s choice among *J* alternatives in choice situations *s* provided that the individual resides in class *C* is the one that provides the highest utility, similar to expression (2).

$$U_{jit} = \alpha_j + \beta_c x_{jis} + \varepsilon_{jis} \qquad (3)$$

Notice that $\beta_{c's}$ are now specified as a class specific parameter vector. Latent class, like MNL induces the restrictive IIA property within classes. Thus, the model form can be considered semi-restrictive. We now move to the most recent development among RUMs which effectively harnesses both the advantages of GEV and latent class, providing an omnibus solution to the restrictions of MNL.

Mixed logit (ML) has been heralded as a major breakthrough in the modelling of discrete choice (Train 1998) and has been made possible through improvements in computer speed and simulation techniques (Train 2003). As the name implies ML is effectively a mixture of logits. ML initialises with a basic core MNL then accommodates heterogeneity by iteratively taking draws (r) of β's from some underlying distribution (normal, lognormal, triangular). This procedure is done many times (e.g., r=500) and the results are averaged. The 'mixing" of β's induces correlation in ε_j's which relaxes IID.

Drawing directly from (Greene 2007) (specifications 4 through 6) the starting point is to assume the MNL depiction from (2) this time including ascs and multiple choice situations, *s,* are specified:

$$P(y_{is} = j) = \frac{\exp(\alpha_{ji} + \beta_{ik}'\mathrm{x}_{jis})}{\sum_{q=1}^{J}\exp(\alpha_{qi} + \beta_{ik}'\mathrm{x}_{qis})} \tag{4}$$

The mixed logit model takes form by allowing individual parameter estimates β_i in the vector β. Where:

$$\beta_{ik} = \beta_k + \sigma_k v_{ik}$$

In this formulation β_k is the population mean, v_{ik} is individual specific heterogeneity, with mean zero and standard deviation equal to one. σ_k is the standard deviation of the distribution β_{ik} around β_k. The analyst observes X and estimates β_k and σ_k. The analyst can test whether alternative parametric distributions for β_k and σ_k , e.g., normal, lognormal, uniform or triangular, provide better approximations of population preferences. Specification (4), is also known as random parameters (RP) logit and can be extended to allow for heterogeneity in the random parameter means and variances (heteroscedasticity - Greene, Hensher & Rose 2006). To allow σ_{ki} to be heteroscedastic the specification is extended to:

$$\sigma_{ik} = \sigma_k \exp[\omega_k' hr_i]$$

where ω_k are parameters which capture variance heterogeneity in the random parameters in systematic utility and hr_i are observed variables of the individual (e.g., angler's skill level). The means are allowed to be heterogeneous according to observed variables, z_i of the individual where, δ_k, are parameters which capture the mean shift. B_{ik} can be specified as:

$$\beta_{ik} = \beta_k + \delta_k' z_i + \sigma_k v_{ik}$$

As before, ε represents the unobserved portion of utility. Each individual's level of unobserved utility, ε is random. However, in the mixed logit framework, compared to MNL correlation is induced in ε. This correlation partially relaxes the IID assumption. The ML model can be further generalized to allow variance differences to be captured in unobserved utility at the alternative specific level. These error components completely relax the IID assumption of MNL, allowing individuals' substitution patterns to become fully flexible. In theory error components can be estimated for each alternative and/or in 'nests' which include multiple alternatives, provided that rank and order conditions are met (Walker 2002). [5] Effectively, the simulation procedure is the same for random parameters and error component parameters - draws are taken from a predetermined distribution and the results are average. Parameters are arrived at which maximize the simulated log-likelihood. The error component specification can be estimated in addition to the random parameter specification (4) or while maintaining (2).[6] Below we specify (4) plus error components:

$$P(y_{is}=j)=\frac{\exp[\alpha_j+\beta_{ik}'\mathrm{x}_{jis}+\sum_{m=1}^{M}d_{jm}\theta_m E_{im}]}{\sum_{q=1}^{J}\exp[\alpha_{qi}+\beta_{ik}'\mathrm{x}_{qis}+\sum_{m=1}^{M}d_{qm}\theta_m E_{im}]}, \tag{5}$$

where E_{im} are individual specific random error terms, m=1,……M, $E_{im}\sim$ N[0,1], θ_m is the scale factor for error component m, and d_{jm} is equal to 1 if E_{im} appears in the utility for alternative j and 0 otherwise.

To further generalize (5) to account for sources of heterogeneity (heteroscedasticity) in the distribution of ε_j the model becomes:

$$P(y_{is}=j)=\frac{\exp[\alpha_j+\beta_{ik}'\mathrm{x}_{jis}+\sum_{m=1}^{M}d_{jm}\theta_m\exp(\gamma'_m he_i)E_{im}]}{\sum_{q=1}^{J}\exp[\alpha_{qi}+\beta_{ik}'\mathrm{x}_{qis}+\sum_{m=1}^{M}d_{qm}\theta_m\exp(\gamma'_m he_i)E_{im}]}, \tag{6}$$

where $\exp(\gamma'_m he_i)$ is heterogeneity in the variance of the error terms which are captured by, he_i, characteristics of the individual (e.g., skill level). Specification (6) represents the most flexible RUM (Greene 2007). Searches through the published literature, across disciplines, suggest only one empirical application of this fully extended ML model (Greene and Hensher 2007).

Train (1998) was the first to introduce random parameters logit by investigating damages to recreational trout angling in Montana caused by mining operations (Train 1998). Train found statistically significant variation among angler preferences for fishery attributes with random parameters improving the statistical fit compared to MNL. Since Train's pioneering study models within the ML framework have 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 ML recreational angling applications (e.g., Phaneuf, Kling & Herriges 1998; Breffle, & Morey 2000; Provencher & Bishop 2004). All of these studies have relied on the random parameters specification to explore the extent of, but not the source of heterogeneity in systematic utility. Hynes, Hanley & Scarpa (2008), in a kayaking application, have however gone further by controlling for heterogeneity in means of the random parameters using individual's self-rated level of kayaking skill. Hynes *et al* (2008) found preference intensities for water quality and star quality rating of kayaking sites to be related to skill level. Other studies which decompose random parameter means outside of environmental and recreation studies include Baht (1998, 2000) and Bhat & Zhao (2002). Greene, Hensher, & Rose (2006) go further than these

[5] Order condition (from Walker (2002), where s equals the number of error components which may be estimated: s=J(J-1)/2-1.

[6] The later is referred to as an error component-MNL.

studies by accounting for heterogeneity in the random parameter variances using an empirical study investigating the effect of income and household size on fare, travel time savings and egress time for commuter mode choice. Greene & Hensher (2007) build on Greene *et al* (2006) to add error components to the random parameters specification and determine the extent to which age influences heterogeneity around the variance of the error components. Studies in the environmental and recreation literatures have not, to our knowledge, explored the error components extension to random parameters, or the extensions which control for heteroscedasticity in the random parameter and error component variances.

Survey Design

Revealed preference is 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. Stated preference experimentation is advantageous for understanding New Zealand anglers' choices because the method can overcome problems associated with multicollinearity and lack of variability in attribute levels found in actual fishing sites. Relatively few angling RUM studies have taken advantage of the benefits of stated preference experimentation. Hunt (2005) found that out of 50 studies in the published literature, only three used stated preference data.

The initial step for designing the choice experiment was to decide which fishing site alternatives to use and which attributes to describe them with. In order to compliment ongoing angler research in New Zealand, alternatives names selected were similar to those used in the National Angler Survey categorization system and included Mainstem-Braided river, Backcountry river, Lowland stream and Lake, but excluded Canal and Reservoir fishing site types because they are not prevalent in North Canterbury region and do not sustain substantive levels of usage. Extensive literature reviews and consultation with FGNZ were used to ascertain salient fishing site choice attributes which were relevant to FGNZ management. Focus groups were then used to pare down this list to nine fishing site attributes and to determine realistic attribute levels. The final alternatives, attributes and attribute levels selected 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. The aim of experimental design 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 parameter estimates (Ferrini & Scarpa 2007; Rose & Bliemer 2005; Jaeger and Rose 2008; Scarpa and Rose 2008). For this study a Bayesian D-Efficient design 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, coherancy and choice complexity was also gathered during the pilots and used to refine the survey.

Care was taken to portray realistic scenarios to respondents (Cummings & Taylor 1998). For instance, some fishing site types 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, unrealistic attribute level combinations were not used; in particular, scenarios with high cost accompanying low travel times. In addition, the attribute levels for Didymo present and riparian margin erosion due to stock were unbalanced, occurring one third of the time in the design for each alternative across all choice scenarios to reflect what is currently experienced in practice and to promote realism in the choice task. 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.

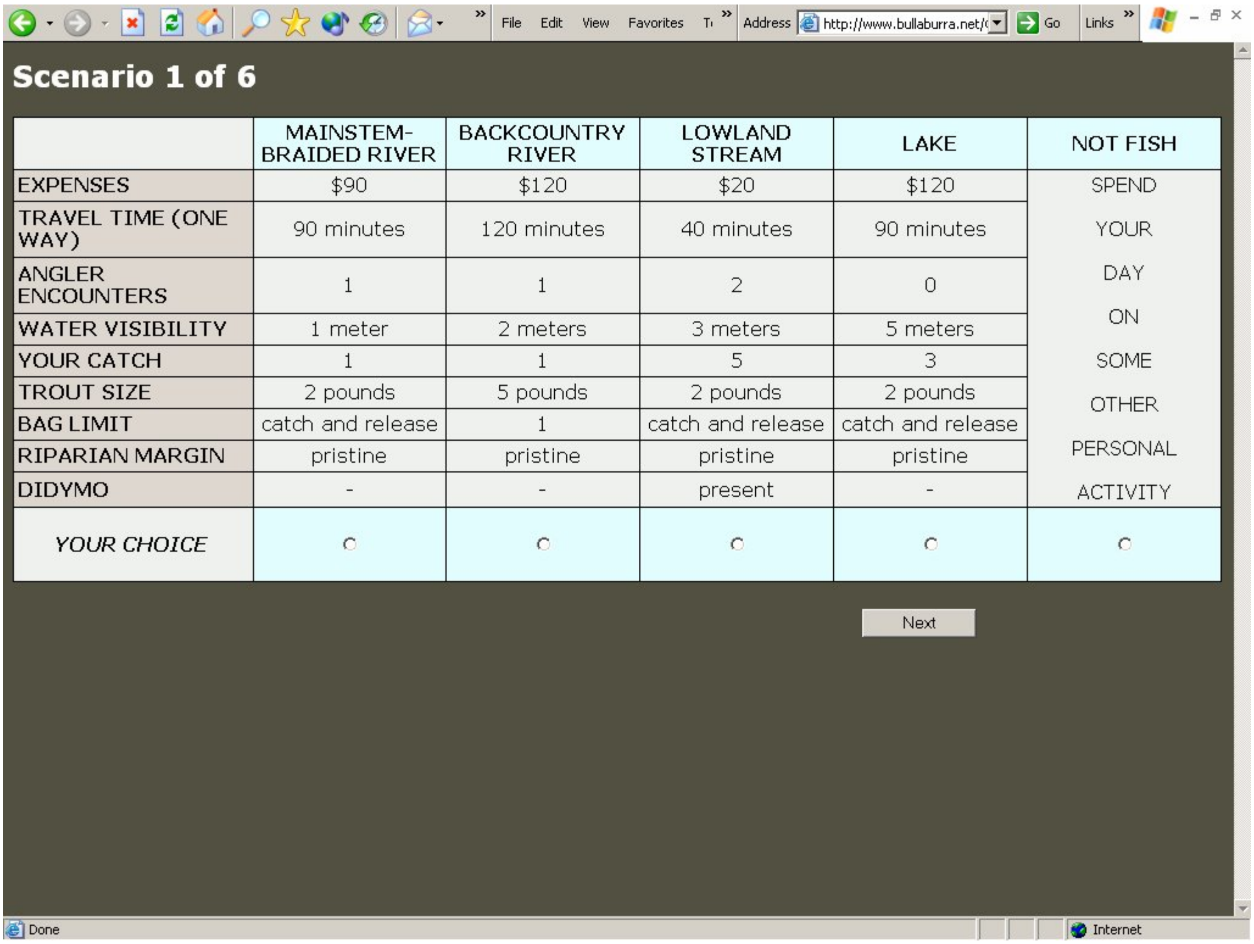
Table 1: Attributes

	Mainstem-Braided River	Backcountry River	Lowland Stream	Lake
Cost (NZD)	\$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, 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, which was chosen over hard copy format due to advantages relating to cost and time savings, consisted of multiple frames informing respondents of the nature of the choice experiment, along with directions and examples for completing the choice scenarios (Dillman 2007). Considerable time was spent in the introduction of the survey describing the nature of the choice experiment, its relevance and fishing site alternatives, attributes and attribute levels. In addition to completing six choice scenarios, each respondent was asked a number of questions relating to their angling background, including their self reported skill level relative to other anglers (beginner, intermediate, expert). The survey was designed to take 15 minutes. In order to motivate participation, respondents were eligible for entry 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
TRAVEL TIME (ONE WAY)	90 minutes	120 minutes	40 minutes	90 minutes	YOUR
ANGLER ENCOUNTERS	1	1	2	0	DAY
WATER VISIBILITY	1 meter	2 meters	3 meters	5 meters	ON
YOUR CATCH	1	1	5	3	SOME
TROUT SIZE	2 pounds	5 pounds	2 pounds	2 pounds	OTHER
BAG LIMIT	catch and release	1	catch and release	catch and release	PERSONAL
RIPARIAN MARGIN	pristine	pristine	pristine	pristine	
DIDYMO	-	-	present	-	ACTIVITY
YOUR CHOICE					

Next

Usable responses were received from 816 of the 6405 people on the FGNZ database who were sent email invitations to complete the survey. These responses resulted in 4896 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, thus the actual response rate is unknown, but it 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 (NZD) 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, 95% 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%).

Statistical analysis

Maximum or simulated maximum likelihood estimation is used in the estimation of logit models. Values of coefficients are arrived at which maximize log likelihood (LL). The higher the LL value (smaller negative number) the better the model fit. The LL ratio statistical test is one means used to statistically test the significance of relative improvements in model fits. LL ratio test = $-2(LL_{\text{base model}} - LL_{\text{estimated model}}) \sim \chi^2$ (difference in the number of parameters). The McFadden R-squared = $1-(LL_{\text{estimated model}}/ LL_{\text{base model}})$ statistical test is the most common test used to measure both overall and relative model fits (Hensher, Greene and Rose 2005). Higher R-squared values suggest a better overall fit.[7] The Akaike and Bayesian Information Criteria (AIC and BIC), are also two additional measures which can be used to compare models with different numbers of parameters, although AIC and BIC have been known to provide differing results as to the optimal model, specifically within the context of latent class modelling.[8] The AIC is a relative measure of improvement in LL with respect to an increase in the number of parameters estimated. AIC=(-2LL + 2k)/n, where k = is the number of parameters and n is the sample size. BIC=(-2LL +k*ln(n))/2. With AIC and BIC lower scores are preferred.

Table 2 presents results from a MNL model (M1) and a three-class latent class model (M2).

[7] It is important to note that the McFadden R-squared statistical test is not analogous to the R-squared statistical test used in ordinary lest squares estimation.

[8] Drawing heavily from Hynes et al (2008) we note that, "with respect to the definition and testing of hypothesis on the number of classes in the latent class model the conventional specification tests used for maximum likelihood estimates (likelihood ratio, Lagrange multipliers, and Wald tests) are not valid as they do not satisfy the regularity conditions for a limiting chi-square distribution under the null (Hynes et al 2008 p.10)." Therefore researchers must resort to other statistical information criteria, such as the Akaike Information Criteria (AIC), corrected AIC (crAIC) which penalises for extra parameters estimated, or Bayesian Information Criteria (BIC). "Even though these criteria statistics are very useful in deciding on what the optimum number of classes is, they have been shown to fail some of the regularity conditions (Hynes et al 2008 p.10)." For example Hynes et al (2008) found with the same data set the BIC statistic suggested the existence of six classes, AIC two classes, and crAIC nine! Thus discretion on the part of the researcher is largely needed. In particular, Scarpa and Thiene (2005) state that "the chosen number of classes must also account for significance of parameter estimates and be tempered by the analyst's own judgment on the meaningfulness of the parameter signs."

Table 2: Summary of the MNL and latent class statistical models

	MNL M1		LCM M2					
			Class 1		Class 2		Class 3	
Attributes								
Cost	-0.007	***	-0.007	***	-0.007	***	-0.007	***
Travel time	-0.006	***	-0.007	***	-0.007	***	-0.007	***
Water visibility	0.049	***	0.081	***	0.063	***	-0.005	
Catch	0.111	***	0.274	***	0.075	***	0.003	
Trout size	0.159	***	0.288	***	0.172	***	0.100	***
Bag limit	0.188	***	0.051		0.351	***	0.045	
Riparian margin	-0.412	***	-0.335	***	-0.418	***	-0.730	***
Didymo	-0.273	***	-0.091		-0.329	***	-0.636	***
Encounters	-0.033		-0.227	***	0.081	***	-0.047	
Mainstem river asc	0.128		0.883	*	-0.296		0.925	***
Backcountry river asc	0.603	*	2.170	***	-0.897	***	1.939	***
Lowland river asc	-0.158		0.845	*	-0.592	***	-0.075	
Lake asc	0.128		0.651		-0.857	***	2.193	***
Constant			-0.367		1.280	***	0.000	**
Skill			0.644	***	-0.454	**	0.000	**
Class Probability			0.317		0.475		0.208	
Parameters	13		39					
AIC	2.942		2.801					
BIC	2.959		2.852					
LL	-7144.692		-6816.690					
McFadden R-sqrd	0.0518		0.1349					

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

Parameter estimates in M1 carry expected signs. Higher cost and greater travel time were both evaluated negatively, as were damaged riparian margins and didymo infestations. The parameter for encounters with other anglers was negative but not significant. Higher water visibility was evaluated positively, as was catching more trout, bigger trout and bag limits. The ascs capture 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*, unobserved utility associated with the Backcountry river utility function is greater than the utility received by not fishing.

M2 reported in Table 2 incorporates a limited degree of both observed and unobserved angler heterogeneity. The three-class model is presented here; four and more-class models may allow for further discrimination. M2 is preferred over M1 on AIC, BIC, McFadden R-squared and the likelihood ratio test criteria ($\chi 2$=656.544; df =26; $p<0.00001$) and reveals significant preference heterogeneity not uncovered by M1. The probabilities of anglers falling in to class One, Two or Three were 31.7%, 47.5% and 20.8% respectively. Both the cost and travel time parameters were fixed across the three classes to provide a base of comparison. Skill level was an important determinant of class allocation, with class one positively associated with more skilled anglers while class two was negatively associated with more skilled anglers. The interpretation is that anglers in class one are tending to be mostly skilled while those in class two are tending to be relatively unskilled. Class three skill level parameters were fixed as the base from which to provide comparison. Some very noticeable preference structure differences emerge between the latent classes. Class one anglers had relatively stronger preference intensities for water visibility, catch rate and trout size compared to the other classes. Anglers in class one view angler encounters negatively, while class two anglers view angler encounters as positive. Bag limits are not a statistically significant influence on the choices of class one anglers while Bag limits were positive and significant for class two anglers. Didymo and riparian margin, where statistically significant, are negative influences on anglers fishing site choices, with class three anglers relatively most averse.

Table 3 presents results from M3, a mixed logit-error component model, M4 which is M3 plus heterogeneity around the error component variances and M5 which is, M4 plus heterogeneity around the means and variances of the random parameters in systematic utility.

Table 3: Summary of the Mixed Logit Statistical Models

	ML M3		ML M4		ML M5	
	Mean	Stdev.	Mean	Stdev.	Mean	Stdev.
Attributes						
Cost	-0.006 ***	fixed	-0.005 ***	fixed	-0.010 ***	fixed
Travel time	-0.004 ***	fixed	-0.004 ***	fixed	-0.009 ***	fixed
Water visibility	0.117 ***	0.117 ***	0.118 ***	0.118 ***	0.050 **	0.050 **
Catch	0.227 ***	0.227 ***	0.228 ***	0.228 ***	0.156 ***	0.156 ***
Trout size	0.341 ***	0.341 ***	0.343 ***	0.343 ***	-0.009	0.009
Bag limit	0.212 ***	1.007 ***	0.212 ***	1.003 ***	0.323 ***	1.143 ***
Riparian margin	-0.631 ***	0.631 ***	-0.632 ***	0.632 ***	-0.637 ***	0.637 ***
Didymo	-0.471 ***	0.471 ***	-0.471 ***	0.471 ***	-0.553 ***	0.553 ***
Angler encounters	-0.022	0.684 ***	-0.020	0.692 ***	-0.023	0.906 ***
Mainstem river asc	-1.193 ***		-1.220 ***		0.198	
Backcountry river asc	-1.325 ***		-1.423 ***		0.642 *	
Lowland river asc	-1.431 ***		-1.454 ***		-0.204	
Lake asc	-1.694 ***		-1.726 ***		0.005	
Heterogeneity around the means of RPs						
Water visibility *Skill					0.021	
Catch * Skill					0.012	
Trout size * Skill					0.212 ***	
Bag limit * Skill					-0.096 **	
Riparian margin * Skill					0.021	
Didymo * Skill					0.102 **	
Angler encounters * Skill					-0.033	
Heterogeneity around the std of RPs						
Water visibility * skill					0.000	
Catch * skill					0.930 ***	
Trout size * skill					2.255 *	
Bag limit * skill					-0.140	
Riparian margin * skill					0.534 ***	
Didymo * skill					0.568 ***	
Angler encounters * skill					-1.038	
Error components						
(Mainstem, Lowland) nest		0.848 ***		0.710 ***		0.746 ***
Backcountry river		1.313 ***		0.959 ***		0.921 ***
Lake		1.258 ***		1.219 ***		1.050 ***
Heterogeneity around the std of the error components						
(Main,Low) * Skill			0.157		0.138	
Backcountry river * Skill			0.262 **		0.337 ***	
Lake * Skill			0.018		0.180 **	
Parameters	18		21		35	
AIC	2.764		2.764		2.734	
BIC	2.788		2.792		2.780	
LL	-6749.226		-6745.517		-6657.407	
McFadden R-sqrd	0.1435		0.1439		0.1551	

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

All mixed logit models M3-M5 were estimated using triangular distributions. Constraints were placed on spread parameters, (and hence on heterogeneity), for the water visibility, catch, trout size, riparian margin and didymo parameters so that the spread parameters (standard deviations of the triangular distributions) would equal the mean values of the distributions. This procedure restricts the sign of the distribution to one side of zero and affords a behaviorally sensible estimate where such an outcome is expected a priori. The constrained triangular distribution is gaining popularity in the literature over other distributions (such as the lognormal) which attempt to achieve the same result but can be difficult to estimate and result in unrealistically long tails (e.g., Greene and Hensher 2007). Parameter estimates from the latent class model were used to inform the selection of which parameters to constrain and which ones not to. The bag limit and angler encounter parameters were not constrained. 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). The primary interest of this research are related to the relative influences of fishing site attributes on angler choice and in the spirit of parsimony the cost and travel time parameters were estimated as fixed parameters. The estimation of M3-M5 was a time consuming process whereby various numbers of draws, r were specified to determine parameter stability (Chiou and Walker 2007). Parameter stability and was achieved when r=750.

Based on statistical criteria (e.g., AIC, BIC and the McFadden R-squared) M3 offers an improvement in fit over the latent class model (M2). M3 has less than half the number of parameters (M3; k=18) compared to (M2; k=39) and a higher LL. Similar to M1, all parameters in M3 have expected signs and are significant except for angler encounters which was non-significant. However, the spread parameter for encounters was statistically significant, indicating wide ranging preference heterogeneity among anglers for angler encounters-some anglers view angler encounters very negatively, for others the effect of encounters is innocuous and others view angler encounters positively. This finding was concealed by the MNL model.

The ascs for all fishing site alternatives are statistically significant with a negative sign. This result may seem slightly counter-intuitive, however one must bear in mind that this does not suggest that, all things considered, anglers prefer the not fish option. Instead the negative ascs suggest that the mean effect of the influences which we have not accounted for systematically (i.e., with attributes such as catch, trout size, Didymo and so forth) have relatively less utility than the not fish option. What is of empirical interests is change in the relative signs in the asc's from the MNL specification to that of the mixed logit specification in M3. Because MNL parameter estimates can only capture means, heterogeneity around that mean is forced into the IID error terms. M3, because it accounts for random heterogeneity effectively recovers this behavioral information from the unobserved effects. The plausible explanation for the observed sign switching is that M3 was able to systematically explain relatively more of the positive influences on individual's site choice, thus leaving content which on average had less utility then the not fish option. M3 specified three error components, although more could have been specified according to Walker's (2002) order condition. One of these error component structures combined the Mainstem-braided river and Lowland stream alternatives (Main, Low). The reasoning behind this decision related to the relative commonalities in scenic and environmental features found in many Lowland streams and Mainstem rivers when contrasted with Backcountry rivers and Lakes. The two other error components were non-nested, and captured the standalone unobserved utility variances for the Backcountry River and Lake alternatives. All error components are statistically significant, which shows that there is a substantial amount of preference heterogeneity associated with the fishing site alternatives not accounted for by the random parameters. The relatively larger coefficient on the Backcountry river error component, compared to the (Main, Low) error component and

Lake error component indicates that there is greater alternative specific variance heterogeneity (heteroscedasticity) in the unobserved effects for the Backcountry river alternative and likewise for the Lake alternative compared to the Mainstem-braided and lowland alternatives.

M4 extends M3, by controlling for error component heteroscedasticity using anglers' self reported skill levels. The Backcountry*skill parameter is positive and statistically significant and suggests that anglers with higher skill level have greater unobserved utility variance than less skilled anglers. The (Main,low)*skill and Lake*skill parameters are positive but not statistically significant, which suggests that a relationship between skill level and unobserved utility variance does not exist for those respondents. M4 offers an improvement in fit over M3 ($\chi2$=7.418; df =3; p=0.0597.

M5 further extends M4 ($\chi2$=176.22; df =14; p<0.00001) by adding two additional sources of information: controlling for heteroscedasticity in the variances of the random parameters and controlling for heterogeneity in the random parameter means, again using anglers' skill levels. The model reveals that as angler skill level increases, preference intensities for catch become greater, and aversions for Didymo infestation decrease in intensity. The negative coefficient on the Baglimt*skill parameter suggests that as angler skill level increases preference intensities for the option to take an additional trout home decrease or become negative. The heteroscedasticity parameters capture additional source of angler heterogeneity in the variance estimates of the random parameters. The positive and statistically significant signs for the catch*skill, troutsize*skill, Didymo*skill and riparian margin*skill show that as angler skill level increases so too does the variation in preferences for the respectively named attributes. For example, this would suggest that there is greater preference heterogeneity among skilled anglers for catch rates, trout size, Didymo infestation and riparian margin erosion, compared to anglers with lower skill level. The asc in M5 for backcountry river is positive and statistically significant, which indicates the mean effect of what is not accounted for in systematic utility, is on the average, positive. No other ascs are statistically significant.

Predictive Performance

The advanced logit models elucidated, to varying degrees, both the extent and source of preference heterogeneity among North Canterbury anglers. To test model performance, so far, we have relied on statistical criteria such as the LL ratio test, R^2 and the AIC. For all cases the more advance logit specifications, despite additional parameters, significantly improved model fit, with M5 performing the best.

To further explore the performance of the different RUMs a scenario is simulated and the models M1-M5 are used to forecast the change in the probability of choosing each alternative from pre to post scenario (effectively revealing direct and cross-elasticities). We chose a scenario which very roughly simulates the environmental disturbance which has occurred on North Canterbury Lowland streams: 50% decrease in water visibility, 50% decrease in catch rate and presence of riparian margin erosion due to stock. We assume that all other fishing site alternatives are unaffected. It should be noted that the values reported here are based on an un-calibrated stated preference choice model, and do not reflect actual market shares. Thus caution should be exercised when interpreting the actual choice probabilities. However, the primary interest here is to investigate the change in behavioural response (captured by choice probabilities) which are forecast by the various logit specifications. If non-proportional substitution patterns are present we would expect the advanced logit specifications to reflect these in contrast to M1 which maintains IIA.

Table 4 presents the pre-scenario and post scenario predicted choice probabilities along with the percentage change in choice probability for each alternative (last column) given the scenario which assumed degradation to Lowland stream water visibility, catch rates and riparian margins. Briefly, given the environmental disturbances M1 predicts that the probability of anglers selecting the Lowland stream alternative decrease by -48.22% while the probability of selecting the Mainstem-braided river, Backcountry river, Lake and not-fish option increase by 12.90%, 13.36%, 11.76% and 12.47%, respectively. The first point of interest is the relative degree to which the Lowland stream choice probability decreases. This figure is not far off the actual 60% decline evidenced by the National Angler Survey as reported in the introduction. Secondly, M1 clearly maintains relatively proportional substitution patterns, which is an artefact of the restrictive IIA property.

The M2 latent class model allowed a limited degree of angler heterogeneity to be revealed as well as a partial relaxation of the IID property (IIA is still maintained within classes). M2 predicts a change in probability of selecting the Lowland stream alternative of -48.73%, which is almost identical to M1. However, M2 predicts non-proportional substitution patterns with choice probabilities increasing for the Mainstem-braided river, Backcountry river, Lake and not-fish options by 15.80%, 11.61%, 10.39%, 18.15% respectively.

The mixed logit model M3 predicts choice probability changes distinctly different to M1 and M2. Firstly, M3 predicts a 62.55% reduction in anglers selecting the Lowland stream alternative, which is noticeably larger than M1 and M2 and much more in line with the National Angler survey reports. Secondly, M3 predicts the highest rate of substitution to Mainstem-Braided river alternatives. Substitution to the Backcountry river and Lake alternatives are relatively lower but have similar rates. M4 which controls for unobserved heterogeneity at the alternative level predicts a pattern of substitution very similar to M3. M5, which controls for heterogeneity in the random parameter means and heteroscedasticity in the random parameter variances and error component variances, predicts a 52.85% reduction in choice probability for the lowland stream alternative, and non-proportional substitution patterns tending toward the Mainstem-braided river option.

Table 4 Scenario: Lowland stream degradation

	Pre-scenario	**Post-scenario**	
MNL M1	Choice probability	Choice probability	% change in choice probability
Mainstem	21.81%	24.63%	12.90%
Backcountry	30.62%	34.71%	13.36%
Lowland	20.96%	10.85%	-48.22%
Lake	17.01%	19.02%	11.76%
Not Fish	9.60%	10.80%	12.47%
Total	100.00%	100.00%	
Latent Class M2			
Mainstem	23.11%	26.76%	15.80%
Backcountry	30.21%	33.72%	11.61%
Lowland	21.42%	10.98%	-48.73%
Lake	16.86%	18.61%	10.39%
Not Fish	8.41%	9.93%	18.15%
Total	100.00%	100.00%	
Mixed logit M3			
Mainstem	21.81%	26.71%	22.44%
Backcountry	30.64%	34.93%	14.01%
Lowland	21.01%	7.87%	-62.55%
Lake	17.28%	19.60%	13.42%
Not Fish	9.25%	10.89%	17.66%
Total	100.00%	100.00%	
Mixed logit M4			
Mainstem	22.12%	27.13%	22.68%
Backcountry	29.74%	34.04%	14.45%
Lowland	21.31%	7.96%	-62.64%
Lake	17.43%	19.80%	13.61%
Not Fish	9.40%	11.07%	17.71%
Total	100.00%	100.00%	
Mixed logit M5			
Mainstem	21.73%	25.85%	18.94%
Backcountry	30.24%	33.86%	11.97%
Lowland	21.10%	9.95%	-52.85%
Lake	17.51%	19.60%	11.92%
Not Fish	9.42%	10.74%	14.04%
Total	100.00%	100.00%	

Discussion & Management implications

The application of discrete choice analysis to study North Canterbury trout angler's fishing site choice(s), has been the result of a long period of investigation of the sources of influence on anglers' behaviour. 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 with extended mixed logit models, is a complex statistical task requiring a large amount (Munizaga and Alvarez 2005) of high quality data (Cherchi and Ortuzar 2008; Greene and Hensher 2007). Internet application, while incurring substantial setup costs, allowed a large amount of data to be collected relatively quickly and cheaply.

Background data collected on anglers suggests that the majority of anglers fishing North Canterbury use multiple types of sites and methods while fewer anglers tend to target one type of fishing site to the exclusion of others. On the whole this indicates a relatively flexible population likely to be willing to transfer activity between locations according to conditions. Although some anglers have strong preferences for particular waters the advanced logit models (M3-M5) indicate that anglers on the whole are indeed willing to transfer their fishing effort to alternative sites and that this pattern of substitution is non-proportional. The implication is that loss of some waters has the potential to dramatically increase angler pressure on other waters.

Further, 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). It was clear from this research that while the latent class model was able to identify finite preference differences between anglers the ML models (M3-M5) provided a much richer understanding of preference heterogeneity by revealing population preference profiles over a continuous distribution.

In the past researchers believed that ML was limited in its capacity to reveal sources of heterogeneity. For instance, "while these procedures [mixed logit] incorporate and account for heterogeneity, they are not well-suited to explaining the sources of heterogeneity (Boxall & Adamowicz 2002, p. 422)" and "although the random parameters approach is useful to assess the extent of preference heterogeneity, the typical absence of an explanation for the source of preference heterogeneity limits the usefulness of the approach for managers (i.e., one typically assesses the extent and not the causes of the variability in preferences)" (Hunt 2005, p.160). Extensions to the mixed logit model adopted here overcome these limitations.

ML extensions identified that random heterogeneity both in the random parameters and error components, which could be explained by angler skill level. While the models reported here systematically explained some of the random heterogeneity captured in the ML models with angler skill level they could have investigated other relevant angler characteristic information, such as income, gender, area of residence (foreign or domestic) or level of recreation specialisation (Bryan 1977).

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. Though we use just one of the constituent dimensions of specialisation, skill level, our findings are consistent with Bryan's (1977) hypotheses using both M2 and M5. For M2 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, are averse to encounters with others, are not concerned with bag limits and prefer to catch larger trout. The positive signs on the trout size, water visibility parameters and negative signs on the encounters and bag limits parameters for Class One anglers are consistent with Bryan's conjecture that specialised anglers have strong preferences (and positive) for larger size fish, 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. M5 revealed similar findings -as anglers increase in skill preference intensities for trout size increase and for bag limits decrease. Further anglers become less averse to Didymo infestation. This later finding, which was also identified by M2, is in contrast to what specialisation theory suggests, i.e., anglers become more sensitive to resource disturbance with increasing specialisation. Research on ecological effects of Didymo on invertebrate density, dynamics and trout stocks and so forth, are limited at this point in time, because Didymo is such a recent phenomenon. However, there have been some anecdotal reports from anglers suggesting that trout stocks (in some cases) may actually benefit from Didymo infestation due to higher invertebrate densities. If this is true then perhaps more highly skilled anglers, are more astute to these collateral benefits and as a result have less of an aversion to Didymo.

The finding that more skilled anglers have greater variance heterogeneity in unobserved utility at the alternative level is of empirical interest and in line with recent recreation specialisation research (Kuentzel & Heberlein 2006) which suggests that as individuals' specialise they follow multiple trajectories, preferences become more refined and load on to a greater number of factors (attributes). In the context of a RUM, the more factors which enter individuals' decision processes, (yet are not accounted for systematically) the greater the amount of content which will reside in unobserved utility. Therefore, it is not an altogether surprising finding that individual skill level is positively related to variance heterogeneity for the Backcountry and Lake error components in M5.

The next challenge for analysis of this data set will be to investigate the explanatory power of composite measures which capture angler specialisation instead of the uni-dimensional skill measurement used in this paper. The recreational specialisation construct has strong historical support in the literature, however, an ongoing debate exists as how best to operationalise the construct, i.e., which measures are most salient for explaining recreationists preference diversity. "Beyond the recognition that recreational specialisation includes a set of behaviours and attitudes, there remains little agreement about how precisely to characterize and measure the construct" (Scott & Shafer 2001, p.325-326). The ML extensions used here provides a powerful framework for carrying out this investigation.

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