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The Value of Fish 'n' Trips to Recreational Anglers in Southern Western Australia.

by Martin van Bueren

Department of Agricultural and Resource Economics
University of Western Australia
Nedlands 6907
Western Australia

email: mvbueren@cyllene.uwa.edu.au

Abstract

Key words: Random utility model, allocation policy, fisheries management.

Recreational fishing is one of the most popular forms of outdoor recreation in Australia, involving approximately a third of the population. As such, the recreational sector is a significant user of fish stocks and coastal areas. Allocating resources fairly and efficiently between recreational anglers, commercial fishermen, and other users has become a major issue in fisheries management. Because there is no market to signal the values of recreational fishing, there is a tendency for fish and access to beaches for recreation to be under-supplied. Managers are aware that recreational fishing provides substantial social and economic benefits, but do not have a good grasp of their magnitude or sensitivity to changing conditions. This paper presents the results of an empirical study which estimates the value of fishing trips made by a sample of shore anglers, together with their marginal values for several types of fish. Welfare estimates were obtained using a random utility model which infers values from anglers' observed choices of site and target species. The average consumer surplus from a day trip was estimated to range between \$33 to \$39, while improving catch rate by 50% increased the value of a trip by up to \$4 depending upon the type of fish affected by the change. Based on the average number of fish caught per trip, this equates to a marginal value of \$1.40 per fish. This study demonstrates that the random utility model is a promising new technique for deriving non-market values and assessing policies that allocate natural resources between user groups.

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Introduction

Recreational fishing is a leisure activity that has gained widespread popularity in most of the world's developed countries. Recent surveys conducted in Australia indicate that 6 million people, or 34%, of the nation go fishing at least once a year (McGlennon 1994). Similar participation rates have been reported for the United States, Canada and Sweden (Cunningham, Dunn et al. 1985). This growth in demand for recreational fishing has prompted government fishery agencies to explicitly consider the activities of amateur fishers in their management plans. Whilst managers have traditionally focused their efforts on commercial harvesting, there is now a growing awareness that the recreational sector is also a significant stake-holder and needs to be taken into account when formulating policies.

More is becoming known about the biological impact that recreational fishers have on fish stocks. Surveys are revealing that recreational catch and effort is substantial in some Australian fisheries, and sometimes exceeds that of the commercial sector (Hancock 1994). Amateur anglers have gradually become more efficient at catching fish: "Serious" anglers are often equipped with an electronic fish-finding device, a four-wheel drive vehicle and portable freezer. This has led to some popular recreational species in Western Australia being over-exploited[1]. Consequently, it is now commonplace for the recreational sector to be regulated by means of bag limits, size limits, gear restrictions, closed areas, closed seasons, and licences.

Less is known about the economic and social values associated with recreational fishing. Unlike commercial fishing, there is no market for establishing the size of recreational benefits and catch is not the only factor influencing welfare. A large proportion of the benefits from recreational fishing are probably derived from intrinsic aspects of the fishing experience. On the basis of expenditure estimates, the economic benefits could be significant. For instance, it is estimated that West Australian anglers spend in the order of $300 million per annum on fishing related goods and services (Lindner and McLeod 1991)[2].

A better understanding of the preferences and values of anglers is essential if we are to effectively address many of the management issues that are pertinent to amateur fishing. Briefly, these include:

- the allocation of resources between user groups
- policies and programmes for protecting fish stocks
- strategies to enhance the value of recreational fishing
- the cost of pollution to recreational fishers
- pricing policies for recreational fishers

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[1] Western Australia Recreational Fishing Advisory Committee (1990). The Future for recreational fishing: Issues for community discussion, Fisheries Department of Western Australia.

[2] Estimate adjusted to 1998 dollars using 16.7% inflation since the survey was conducted.

Little work has been done in Australia towards developing an economic framework that is capable of evaluating these issues. Many expenditure studies have been commissioned and several input-output analysis have been undertaken as a means of assessing the impact of recreational fishing on regional economies (eg. Lindner and McLeod 1991). However, studies of this type do not provide a basis on which to assess the economic efficiency of policies that affect anglers. What needs to be measured is anglers' willingness to pay for fishing over and above their costs, which is equivalent to consumer surplus. Only a handful of Australian studies have quantified this welfare measure (eg. Staniford and Siggins 1992; Burns, Damania et al. 1997; and Blamey 1998). These studies have only had limited success at eliciting reliable estimates of consumer surplus. Their authors unanimously recognise that further work needs to be done to refine the methods of non-market valuation.

This paper contributes to this refining process by drawing upon some of the techniques that have been developed in the United States for modelling recreation demand. In particular, the random utility model is evaluated as a means of estimating consumer surplus and describing the behaviour of anglers in southern Western Australia. The paper extends the literature on non-market valuation by demonstrating that the model results are sensitive to different specifications of catch rate, a major variable in the individual's utility function. It concludes by postulating about the future role of non-market valuation in fisheries management.

Modelling Framework

Various survey techniques have been used in the past to estimate the consumer surplus associated with recreational fishing. All the techniques centre on the individual angler and either impute values by observing people's actual visits to recreation sites (eg. the travel cost method) or by asking respondents to state their preferences for hypothetical goods (eg. contingent valuation). In the context of recreational fishing, the goods typically valued are a day of fishing, annual access to a fishery, or an improvement in catch rate.

The travel cost method uses angler's visits to fishing sites, and their associated travel costs, to impute a demand function for fishing. An annual measure of consumer surplus is subsequently calculated by integrating the function. While this technique has been employed extensively in the past (eg. Sorg and Loomis 1986; Loomis 1989; Milon 1991), it suffers some serious limitations. In particular, it is weak at valuing changes in quality, which means that it cannot be used to produce robust estimates of the marginal value of fish (Bockstael, McConnell et al. 1991). This renders the technique ineffective at assessing many of the issues that are of interest to fishery managers.

The contingent valuation method emerged partly out of a desire to avoid the econometric difficulties that are inherent in travel cost modelling. Instead of imputing values from observations of angler's behaviour, it asks respondents to directly state their willingness to pay for access to a fishing site or an improvement in quality. However, this method has its own set of difficulties. Neither the dichotomous or open-ended versions of the technique adequately account for substitutes[3]. In the case of recreational

[3] Contingent valuation questions were traditionally open-ended. Using this approach respondents are asked directly how much they are willing to pay for a good. Dichotomous choice questions are now

fishing this is a real problem because it is common for anglers to have access to many different sites and species of fish. When contingent valuation has been used in the past, it has been found that respondents tend not to not allow for the availability of substitutes when answering the bid question, thereby over-stating their true willingness to pay (Boxall, Adamowicz et al. 1996). Researchers have also found that respondents possibly interpret a specific increase in quality as symbolic of "better quality all round" without paying attention to the actual size of the increase (Blamey 1998). This is thought to be one of the main culprits responsible for lack of sensitivity to scope when different sub-samples of respondents are asked to value different levels of quality.

A third limitation exists because contingent valuation is divorced from a model of behaviour. Consequently, it cannot examine the extent to which anglers alter their trip frequency or redistribute their trips across sites and species following a change in fishing conditions. This is precisely the type of information needed by managers to judge the likely effectiveness of regulations designed to protect stocks.

Over the last five years or so an alternative valuation technique known as the random utility model has come to the forefront. It has some obvious advantages over the travel cost and contingent valuation methods. It is able to explicitly account for substitutes, measure the impact of quality attributes on utility, and describe the choice behaviour of anglers (Bockstael, McConnell et al. 1991). The random utility model is a revealed preference technique that utilises individuals' discrete choices of site and fish species to infer values for these goods. It assumes that an individual's choice behaviour is driven by utility maximisation theory. Parameters of the utility function are estimated by observing the tradeoffs that are made by respondents when they choose between sites of differing quality and travel cost.

The study presented in this paper adopts a multi-stage framework for describing an individual's demand for fishing (Figure 1). A random utility model (RUM) is central to this framework. It estimates parameters of each individual's utility function which are required for deriving "per trip" consumer surplus values. The other stages of the framework are a catch rate function and a trip demand function. Trip frequency was modelled with a separate function because the RUM cannot easily describe an individual's demand for trips over an extended period of time[4]. Following an approach developed by (Bockstael, Hanemann et al. 1987), the trip function was linked to the RUM via an "inclusive value index" which is a parameter from the RUM that measures an individual's expected maximum utility per trip. In this way, an improvement in site quality increases the value of the index which, in turn, increases the predicted number of trips.

One of the main attributes hypothesised to influence an individual's choice of fishing site was expected catch rate. Catch rates were predicted using a production function, as represented by the first stage in Figure 1. This function allows for the fact that anglers are able to influence their level of success at a site by combining their time, skill and

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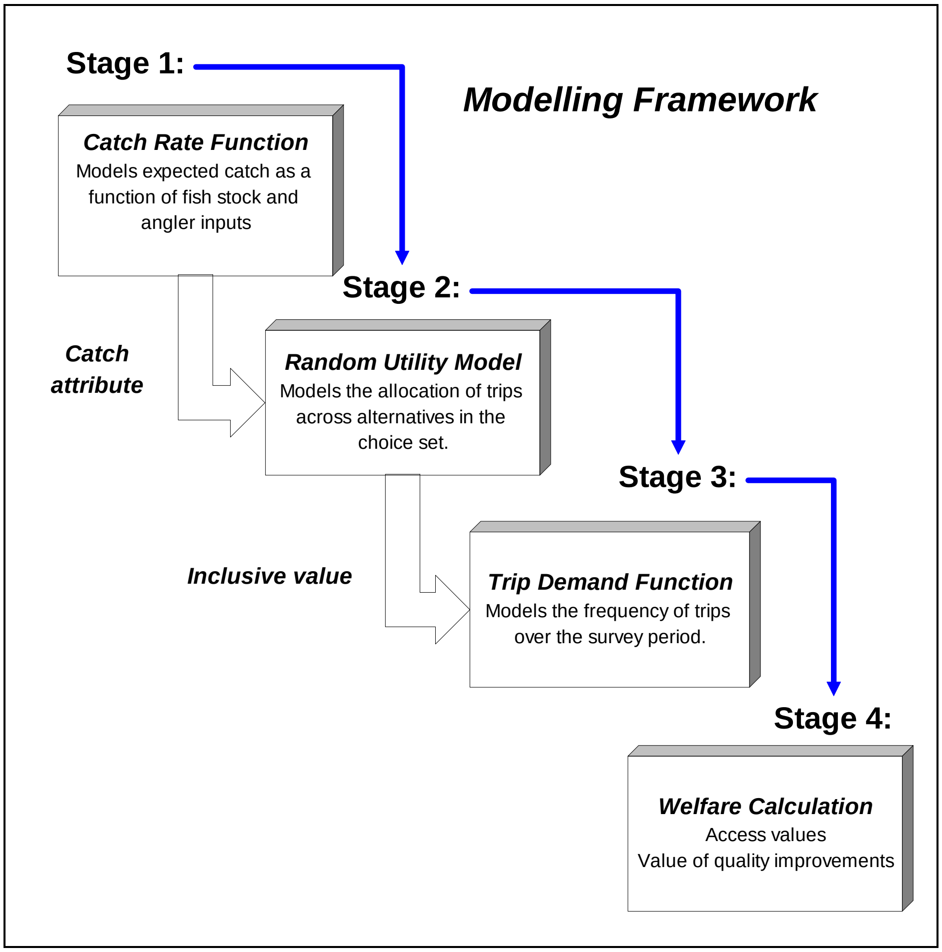
preferred by researchers. This format simply requires respondents to either accept or reject an "offer amount" in return for an improvement in quality or continued access to a fishery.

[4] Trip frequency can be estimated by a RUM if a participation decision is included as a choice alternative and weekly decisions are observed over a period of time. This version of the RUM is known as a repeated discrete choice model. For an application of this model to recreational fishing see Morey, Rowe et al. (1993).

equipment with fish stocks. Previous work by McConnell, Strand et al. (1995) demonstrated the usefulness of formulating an endogenous measure of catch rate rather than restricting all individuals to experience the same level of success at a site.

The final stage of the analysis involved calculating welfare estimates. These calculations use estimated parameters from the utility function to determine an individual's *per trip* benefits from improvements in quality and access to sites. The multi-stage framework allows benefits to be aggregated to the whole survey period using the predicted number of trips from Stage 3.

Figure 1: Overview of the modelling framework used to describe an individual's demand for recreational fishing.



Model Specification

Random Utility Model

To illustrate how the RUM works, consider the situation where an individual has the option of choosing one site from a possible set of J sites on a particular trip. The individual is assumed to choose site j if his/her utility from fishing at site j exceeds that of any other site, i. Because utility is stochastic to the researcher, it is only possible to predict an individual's choice of site j up to the level of a probability. This is given by:

$$\Pr_j = \Pr[\{v_j(q_j, Y - p_j) + \varepsilon_j\} \geq \{v_i(q_i, Y - p_i) + \varepsilon_i\}] \qquad \forall\ j \neq i$$

where $v_j(.)$ is the observable component of utility for site *j*, q_j is a vector of quality attributes of site *j*, *Y* is the individual's per-period income, p_j is the individual's cost of a return visit to site *j* [5], and ε_j is the unobserved component of utility associated with site *j*.

The RUM is made operational by adopting a particular cumulative density function for the unobserved component of utility, ε. If the ε's are independently and identically distributed with a extreme value type I (Weibull) distribution, then the individual's probability of choosing site *j* is given by a ***multinomial logit model*** (McFadden 1974):

$$\Pr_j = \frac{\exp(v_j)}{\sum_{i=1}^{J} \exp(v_i)}$$

Parameters of the utility function are estimated by Maximum Likelihood which finds values for the coefficients that maximise the likelihood of the pattern of choices in sample being observed[6].

The RUM was used to analyse the joint choices of fishing region and target fish type every time a trip was made. Specifically, individual *i*'s indirect utility function for the joint region/target alternative *jk* was given by:

$$V_{ijk} = \beta_0 PRICE_{ij} + \beta_k CR_{jkt} + \beta_1 COAST_j + \beta_2 DIVERSE_{ij} + \beta_3 SIZE_{ij} + \beta_4 HOUSE_{ij} + \beta_5 CONGEST_j$$

where each of the variables are defined in Table 1. Naturally, the price of a visit and congestion should have negative coefficients, while positive signs were expected for the other variables. Expectations about catch rate and the size and diversity of fish in each region should greatly influence an angler's decision to target a particular location and/or fish type. The length of coast line associated with each region was included as a means of minimising the bias that is likely to be introduced by having a different number of minor access points within each site or region (Ben-Akiva and Lerman 1985). With respect to the variable HOUSE, it was reasoned that respondents are likely to favour a particular region for their fishing trips if they own a beach house in that region.

A separate coefficient on the catch rate variable was estimated for each fish type in order to examine whether anglers valued their catch differently depending upon the type of fish. The coefficients for all other variables were assumed to be the same across target groups implying that the influence of the other variables on an angler's utility are independent of his/her target choice.

Table 1: A description of explanatory variables included in the utility function.

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[5] If (*Y*-*p*) enters the utility function in a linear manner, income cancels out upon estimation because income is constant across all alternatives for a given individual. The absolute value of the price coefficient then becomes the implicit coefficient for income as well.

[6] In this study, the software package LIMDEP (Greene, 1995) was used to estimate the multinomial logit model.

Variable	Description
$PRICE_{ij}$	Predicted fuel cost associated with a return trip to region *j* by individual *i*.
CR_{jk}	One of four proxies for the expected catch rate of fish type *k* at region *j*
$SIZE_{ij}$	Individual *i*'s perception of the reliability of region *j* at producing good sized fish (measured on a scale of 1 to 5).
$DIVERSE_{ij}$	Individual *i*'s perception of the diversity of desirable fish species available for capture in region *j* (measured on a scale of 1 to 5).
$CONGEST_{j}$	Congestion index for region *j*, equal to the mean number of anglers observed to be fishing at region *j* during the summer and spring months of 1995-97.
$HOUSE_{ij}$	Dummy to indicate whether or not individual *i* owns a beach house in region *j*.
$COAST_{j}$	Length of coast line (km) associated with region *j*.

One of the primary attributes of interest from a manager's perspective is the stock of fish. It is postulated that anglers also view the availability of fish as a critical element of their fishing trip; they must be satisfied that there is a non-zero probability of catching fish, otherwise they would not opt to go fishing. Owing to the importance of this attribute, four different specifications were formulated to represent anglers' catch rate expectations at a given location. The random utility model was then estimated using each of these measures to investigate which specification produced the best-fitting model.

Ideally, a good proxy for expected catch rate should capture the fact that this attribute is *stochastic*, *variable over time,* and *individual-specific*. It would be even better if the proxy could be replaced with an individual's own expectation of catch rate at each site on a particular day. However, the majority of previous RUM studies of recreational fishing have used mean catch rates achieved by the sample as a proxy for expected catch rate. Others have based their analysis on historical catch rates that were obtained from surveys conducted independently to the economic survey. Both these indices have shortcomings because they are based on objective catch data which may not reflect anglers' catch expectations. Furthermore, they assume that all individuals face the same level of expected success at a given site which is fixed for the whole survey period. These assumptions are clearly unrealistic.

The four specifications of catch rate used in this study were designed to diagnose whether gains could be made by defining catch success as a temporal and individual-specific attribute. Each of the four specifications are listed in Table 2, together with a summary of their properties. The first two measures were mean catch rates. One was a *fixed* mean of angler's catches at each region over the whole survey period, while the other was calculated on a *weekly* basis. Both measures assigned the same expectation to all anglers who visit a given region. A third proxy was obtained by predicting catch rate via a production function. This measure was labelled Q. Unlike the first two measures, it provided an *individual-specific* measure of catch rate based on an objective assessment of fish abundance at each location.

A fourth measure, EQ, was formulated using respondents' own *perceptions* of catch rate. It was thought that this specification should produce the best-fitting model of choice because individuals are motivated to behave according to their subjective assessments of abundance. While it would have been desirable to elicit catch expectations for all regions in the study area prior to every trip, this proved to be too difficult. Instead, pre-trip expectations were only collected for the region at which individuals intended to visit. Expectations were then extrapolated to the other regions using a "perceptions function". Modelling perceptions in this way does have an advantage: It links angler's subjective assessments of a region's "productivity" to objective (measurable) factors, which are more relevant to policy makers.

Table 2: A summary of the four specifications use for the catch rate (CR) attribute in the RUM model, and the properties of each specification.

Proxy:	*Fixed mean catch rate*	*Weekly mean catch rate*	*Predicted objective catch rate.*	*Predicted perceived catch rate*
Notation:	**MCR**	**MCRT**	**Q**	**EQ**
Characteristics:				
Specific for fish type and region?	✓	✓	✓	✓
Time-variant?	X	✓	✓	✓
Individual specific?	X	X	✓	✓
Reflect perceptions?	X	X	X	✓

The catch rate functions

The predicted "objective" measure of catch rate (Q) was generated using an approach similar to that employed by McConnell, Strand et al. (1995) and Kaoru, Smith et al. (1995). These studies assume that an individual's actual catch of fish type *k* at region *j* on a trip in week *t* is the realisation of a random Poisson process with a mean equal to the expected catch per trip[7]. The Poisson probability of catching *n* fish per trip is expressed as:

$$\text{Prob}[\,n\,] = \lambda^{n} e^{-\lambda}/n! \quad \text{for } n = 0,1,2,\ldots \infty$$

In this present study the factors hypothesised to influence the Poisson mean (λ) were the number of hours spent fishing, individual characteristics, and the stock of fish of type *k* at the region in week *t*, as indicated by the mean catch rate achieved by the whole sample (MCRT). Specifically, λ was specified as:

[7] Catch per trip is subsequently converted to a *per hour* measure using total hours spent fishing (THOURS).

$$\lambda = \exp(\beta_0 INPT + \beta_1 STOCK_{jkt} + \beta_2 \ln(THOURS_i) + \beta_3 GEAR_i + \beta_4 YEARS_i + \beta_5 SKILL_i + \beta_6 CLUB_i)$$

where;

INPT =	intercept term
$STOCK_{jkt}$ =	the sample mean catch rate (MCRT) of fish type *k* made at region *j* during week *t*, regardless of whether respondents were targeting that fish type. For anglers not targeting (*k*=0), STOCK = the mean catch rate of *all* fish caught .
$\ln(THOURS_i)$ =	the log of total number of hours individual *i* spent fishing at region *j* on the trip.
$GEAR_i$ =	the value of individual *i*'s fishing gear.
$YEARS_i$ =	the number of years that individual *i* has fished in Western Australia.
$SKILL_i$ =	the self-reported skill level for individual *i*.
$CLUB_i$ =	a dummy variable to indicate whether or not individual *i* is a member of a fishing club.

The perceptions function was specified in a similar manner except that, in the case of perceptions, the dependent variable did not include any zero catch expectations because respondents were asked to nominate their expected (most probable) catch *conditional* upon catching at least one fish. Consequently, the estimation procedure was modified to account for the fact that the distribution of expectations was truncated at zero. The truncated Poisson function is given by:

$$\text{Prob}[\ n\ ] = n \mid n > 0] = (\lambda^n e^{-\lambda} / n!)/\text{Prob}\ [n > 0] \quad \text{for } n = 1,2,\dots. \infty$$

where *n* is an individual's perceived catch per trip of fish type *k* at site *j* during week *t*. To allow for the conditional nature of the elicited value, catch expectations were adjusted downwards by the respondent's stated probability of catching at least one fish, a variable which was also collected prior to every trip.

Expectations were explained using the same set of variables as those in the objective catch function, except the number of hours spent fishing was replaced with "intended hours" and a dummy variable was added to capture the influence of reports in the media about fishing conditions.

Trip demand function

Trip demand was described using a negative binomial model. Like the Poisson function, this is a count model. Count models have been shown to be well suited for explaining trip frequency because trips are integer values, censored at zero (no negative values), and relatively few in number (Hellerstein and Mendelsohn 1993). A negative binomial model was adopted because the data was known to "over-dispersed", a condition where the variance of the dependent variable exceeds the mean[8]. A truncated version of the model was estimated to allow for the absence of zero values in the data which was a consequence of only including active anglers in the sample.

The negative binomial model is a generalised form of the Poisson model and is obtained by introducing an individual unobserved effect (u_i) into the conditional mean number of

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[8] The negative binomial overcomes a restriction of the Poisson function which stipulates equality between the mean and variance (Greene 1997).

trips (λ). Hence, the probability of individual *i* taking T trips, conditional upon taking at least one trip over the survey period is given by:

$$\Pr ob[Trips = T | T > 0] = \frac{(\lambda_i u_i)^{T_i} \exp^{-\lambda_i u_i}}{T_i\,!} * \Pr ob[T > 0] \quad \text{for T = 1,2,….. } \infty$$

The following specification was used to explain the conditional mean number of trips taken by each respondent over a four month survey period:

$\lambda_i = \exp(\beta_0 INPT + \beta_1 EMPLOY_i + \beta_2 INCOME_i + \beta_3 GEAR_i + \beta_4 CLUB_i + \beta_5 YEARS_i + \beta_6 SHORE_i + \beta_7 RETIRE + \beta_8 IV_i)$

where;

INPT =	intercept term.
$EMPLOY_i$ =	a dummy variable to indicate whether or not individual *i* is employed.
$INCOME_i$ =	income category of individual *i*.
$RETIRE_i$ =	a dummy variable to indicate whether or not individual *i* is retired
$GEAR_i$ =	the value of individual *i*'s fishing gear.
$CLUB_i$ =	a dummy variable to indicate whether or not individual *i* is a member of a fishing club.
$YEARS_i$ =	the number of years that individual *i* has fished in Western Australia.
$SHORE_i$ =	the proportion of individual *i*'s trips to the study area that constituted ocean shore-based fishing.
IV_i =	Individual *i*'s mean inclusive value from the random utility model, which represents the expected per trip utility over the survey period.

All variables in the trip demand function were individual-specific. It was postulated that employment and income should have negative signs because anglers with a job generally have less time to go fishing. Conversely, retired anglers have more time available and hence they are likely to fish frequently. The CLUB, GEAR, and YEARS variables were included to capture the respondent's level of enthusiasm in fishing, and should therefore have positive signs. The variable SHORE was included to account for the fact that only shore fishing trips were represented in the sample. It follows that respondents who fished predominantly from the shore should have a higher trip frequency than boat anglers. Finally, an "inclusive value" index from the random utility model was included in the demand function to capture an individual's expected maximum utility from taking a trip in the study area.

Survey Methods and Data

Data for the study was collected by issuing 135 shore anglers with a log book and asking them to record all their fishing trips to the study area over a period of four months. The study area constituted approximately 350 kilometres of coastline and was divided into six geographic regions. Respondents were instructed to indicate both their choice of region and target species every time they made a trip. The south west fishery offers a large variety of fish species to anglers so, in order to reduce the number of alternatives to a manageable number, each species was categorised into one of four "fish types". Anglers were also given the option of not targeting any particular type of fish.

Therefore, respondents were assumed to have a choice set comprising 30 joint alternatives; that is, 6 regions by 5 target options.

Unlike most other log book surveys that have been conducted in the past, this survey collected *ex ante* and *ex post* information about each fishing trip. Before departing on their trip, respondents were asked to record how long they expected to spend fishing, their target fish type, and the quantity of fish they expected to catch. Upon returning from each trip they were asked to record their actual time spent fishing and realised catch. Perceptions about the average size and diversity of in each region were elicited at the commencement of the survey. Full details of the questionnaire and procedures used to design the survey are documented in van Bueren (1999).

A log book method was deemed preferable to an intercept survey or telephone survey because it minimised recall bias and allowed more detailed information to be collected about the weekly activities of anglers. The survey was not administered to a random sample of anglers. Rather, participants were recruited by advertising for volunteers who resided in the metropolitan area of Perth. This approach had the advantage of generating a sample of anglers who were dedicated and enthusiastic volunteers, a necessary prerequisite for a log book survey. It also maximised the chances of obtaining a sample of anglers who focus their efforts on catching certain types of fish, which is helpful for estimating parameters of the RUM.

The response rate for the survey was reasonable, with 86 useable log books returned at the end of the four months[9]. This represented a response rate of 64% which compares favourably to other studies that have used log books to collect data over an extended period (Jones & Stokes Associates 1991 and Adamowicz 1994). The survey yielded 903 trips for analysis, an average of 10.5 trips per respondent. The vast majority of these were day trips (94%). A proportion of the trips had to be dropped from the data set because some region/target alternatives were seldom selected. Instead of including all 30 alternatives in the choice set, the RUM was simplified by retaining only 9 alternatives (3 target options and 3 regions). The eventual data set used to estimate the random utility model contained 671 trips.

Estimation Results

The results show that the RUM is a reasonable framework for describing anglers' choice behaviour. With the exception of the congestion attribute, all of the variables postulated to influence an individuals utility were indeed significant (Table 3)[10]. As expected, the cost of a trip detracted from an individual's utility, while catch rate contributed positively to utility in two of the four specifications. Table 3 reports the estimated coefficients for each of the four models that correspond to particular specifications of the catch rate variable. All the specifications have reasonable explanatory power, as indicated by the adjusted log likelihood ratios which are in the order of 0.29. While this

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[9] Log books were classified as "useable" if the respondent made at least one trip to the study area and made at least one complete entry in the log book.

[10] The variable CONGEST was removed from the model after preliminary runs showed that it was not significant. Other researchers have also had difficulty obtaining significance for this variable. The effect of congestion on utility is ambiguous because it is positively related to other attributes that enhance the attractiveness of a site.

value might seem to be a little low, it should be remembered that a likelihood ratio index (LRI) of 0.2 is approximately equivalent to an R^2 of 0.5 in an OLS regression model (Veall and Zimmermann 1996). Furthermore, other RUM studies of recreational fishing have obtained similar LRI values (Lin, Adams et al. 1996; Berman, Haley et al. 1997 and Kaoru, Smith et al. 1995).

Table 3: Coefficient estimates and diagnostics for four specifications of the multinomial logit model. Values in parenthesis are t statistics.

	Model type, based on specification of the **CR** variable.							
Variable	Fixed sample mean (MCR)		Weekly sample mean (MCRT)		Predicted objective (Q)		Predicted perceived (EQ)	
PRICE	-0.2155	(-10.1)**	-0.2271	(-10.7)**	-0.2401	(-11.0)**	-0.2357	(-10.92)**
CR $_{(TAB)}$	0.0273	(0.14)	0.6227	(5.08)**	0.5442	(6.18)**	1.3101	(4.57)**
CR $_{(BB)}$	-0.1954	(-2.23)*	-0.0082	(-0.11)	0.1881	(2.62)**	0.9760	(3.67)**
CR $_{(NT)}$	-0.0563	(-0.68)	0.1321	(3.04)**	0.2296	(5.27)**	1.016	(4.26)**
COAST	0.0507	(5.11)**	0.0529	(5.31)**	0.0556	(5.50)**	0.0553	(5.50)**
DIVERSE	0.4582	(3.62)**	0.4523	(3.57)**	0.4844	(3.80)**	0.4842	(3.80)**
SIZE	0.7616	(5.69)**	0.7464	(5.60)**	0.7244	(5.46)**	0.7347	(5.55)**
HOUSE	1.1739	(3.31)**	1.176	(3.33)**	1.0710	(3.01)**	1.061	(3.01)**
Observations	671		671		671		671	
L. likelihood	-1054.55		-1051.43		-1044.72		-1050.68	
LRI (adj.)	0.2837		0.2858		0.2903		0.2863	

* denotes significance at 5% ** denotes significance at 1%

The log likelihood ratio index (LRI) is a pseudo R^2 value and is defined as $1-[\log(L_0)-K/\log(L_R)]$, where L_0 is the maximum value of the likelihood function of the unrestricted model, L_R is the likelihood value of the restricted model (ie. all coefficients set to zero) and K is the number of parameters estimated.

There is some concern in the literature about using multinomial logit models to analyse choice data. This is because they suffer from a restrictive property known as the "Independence of Irrelevant Alternatives", or IIA. Put simply, IIA forces the ratio of probabilities associated with choosing any two alternatives to be independent to all other alternatives in the individual's choice set. If this property is violated, then the model parameters estimated by the multinomial logit model will be bias. There is good reason to be concerned about this restriction because there are many instances in recreational fishing where independence between alternatives may not hold. However, diagnostic tests on the models estimated in this study failed to find evidence of IIA violations[11].

Experimentations with different specifications of the catch rate variable produced some interesting results. Whilst there was little disparity between the specifications with regard to overall model fit, the sign and significance of the catch rate attribute was sensitive to the type of proxy used. Notably, gains were made by specifying catch rate (CR) as a time-varying attribute. The model that used a fixed specification failed to produce coefficients on the CR attribute that were significant and/or had the correct sign. This was largely rectified by using weekly means.

[11] The diagnostic test referred to was a Hausman and McFadden (1984) test.

A further improvement was made by substituting individual-specific catch rates for the sample mean. All CR coefficients became highly significant, and the negative sign on the catch rate of Bread and Butter fish (denoted CR_{BB}) became positive. In addition, the magnitude of the catch rate coefficients for each fish type became aligned with prior knowledge about their relative desirability. The coefficient on the catch rate of Table fish (CR_{TAB}) is larger than that of Bread & Butter fish (CR_{BB}), reflecting the fact that Table fish are more highly regarded than Bread & Butter fish.

A priori, it was thought that substituting objective measures of catch rate with perceptions should improve the explanatory power of the choice model as there was a significant difference between respondents' perceptions of the relative abundance of fish at each region and their actual catch rates. However, the incorporation of perceptions failed to improve the model's goodness of fit. A possible explanation is that the perceptions function used to predict catch rates at each region had a very similar specification to the objective catch function. While perceptions did not have an impact on goodness of fit, they did lead to substantially higher coefficients on the CR variable. This observation supports the notion that anglers' place more weight on perceived catch rates relative to objective measures of this attribute. In other words, when choosing a location, anglers are more responsive to changes in perceived catch rates than changes in objective catch rates. As we will see below, this has an important bearing on the estimated value of fish.

Satisfactory estimation results were also obtained from the other stages of the model. The catch functions fitted the data reasonably well (pseudo R^2 of 0.31 to 0.44) and were therefore considered to be adequate for predicting individual catch rates at each region. The function used to describe trip frequency had a similar degree of explanatory power (pseudo R^2 of 0.48). In both functions, the majority of variables were significant and had the expected signs. For the sake of brevity, estimation results are not discussed any further in this paper, but a summary of the results can be found in the Appendix.

Welfare Measurement and Simulation

Welfare estimates were derived from the random utility model using procedures developed by Hanemann (1984) and Small and Rosen (1981). These methods produce a compensating variation measure of welfare which is equivalent to the amount of money required to make an individual indifferent between an initial situation and a new situation after a change in price or quality.

The value of a day trip to the study area was estimated to range from \$33 to \$39, depending upon the way catch rates were specified in the RUM (Table 4). This estimate was calculated by averaging consumer surplus across trips for each individual in the sample, then taking a mean of these values over all respondents. Individual consumer surplus was calculated using the following formula:

$$CS_{iJ} = \frac{1}{\beta}\ln\left[\sum_{j=1}^{J}\exp V_{ij}\right]$$

where J is the total number of alternatives in the individual's choice set, V_{ij} is individual i's utility for alternative j, and β is the absolute value of the price coefficient in the utility function.

Table 4 also reports values for each region in the study area. They were determined by calculating the change in consumer surplus brought about by eliminating a given region from the choice set. Mandurah has a much lower value than the other two regions because it is further from the main population centre of Perth, and hence has the highest travel costs. Note that the sum of region values is considerably lower than the value of the whole study area. This is because the region values were calculated on the basis that individuals have the opportunity to visit other regions should one location be eliminated. Consequently, the value of any one region is lowered by the presence of substitutes.

The bottom half of Table 4 summarises the values for each fish type. These values were calculated by determining the reduction in consumer surplus caused by setting the catch rate of a particular fish type to zero across all regions. The perceptions model produced larger values for fish than the objective specification because its coefficients on the catch rate attribute are larger. It is thought that estimates from the perceptions model should be the most realistic because they are founded on respondent's own assessments of catch rate at each region.

Values for specific fish types showed that the RUM was capable of discerning between anglers' preferences for different fish. Based on the perceptions model, Table fish were valued at $1.70 per trip while the value of Bread & Butter fish was estimated to be $0.94 per trip. Alternatively, these estimates can expressed in terms of marginal values *per fish*[12]. The values then become $0.52 and $0.14 per fish, respectively. RUM studies conducted in the United States have reported values of a similar magnitude, which suggests that the technique is capable of producing reliable measures of consumer surplus.

In interpreting these results, it is important to remember that all values were determined based on the assumption that anglers have substitutes available to them. That is, if the catch rate of a particular fish type is reduced, they are free to choose a different alternative. If reasonable substitutes exist, then the impact of reducing the catch rate of any one fish type is lessened. For managing a fishery, it may be useful to know the value of each fish type in the absence of substitutes. The absolute value of the ratio of coefficients on the catch rate and price variables provides a measure of this value in the form of a "conditional" marginal value (conditional on an individual choosing to target fish type *k* before *and* after a change in catch rate). Based on the perceptions model, these values are $5.56 per Table fish and $4.14 per Bread & Butter fish. As expected, the values are much higher than those in Table 4 which "control" for substitutes.

The *total* value of the fish resource was estimated by simultaneously setting the catch rates of *all* fish types to zero and recalculating consumer surplus. Using this method it was found that fish contributed approximately $8 to the value of a trip. Interestingly, the fish resource itself is only a fraction of the value ascribed to the whole study area. This result implies that policies for maintaining or enhancing the value of recreational fishing should not just concentrate of fish stocks but also consider the amenity value associated with fishing areas.

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[12] To obtain an approximation of the marginal value *per fish*, the per trip measures were divided by the sample mean catch per trip of the corresponding fish type.

Table 4: Estimates of the mean individual welfare ($/angler/trip) derived by anglers from fishing in the south west fishery. Estimates generated from the perceptions version of the random utility model are compared to those from the objective specification.

	Objective Model (Q)	*Perceptions Model (EQ)*
Access values		
Whole study area	32.64	38.79
N^th^ metropolitan region	-	5.16
S^th^ metropolitan region	-	4.41
Mandurah region	-	1.47
Fish values		
All fish	2.56	7.94
Table fish	1.08	1.73
Bread & Butter fish	0.32	0.94
Non targeted fish	0.66	1.38

The RUM was also used to examine the economic impact of two changes in fishing conditions. The first was a 50% increase in catch rates, which could feasibly be brought about by reallocating fish from the commercial sector to the recreational sector. The second was the implementation of entry fees at certain fishing locations. Changes in welfare were aggregated to the population of shore anglers who live in metropolitan Perth. This group of anglers is estimated to annually spend 2.5 million days fishing[13].

Changes in quality and access price are likely to affect both the value of fishing on a per trip basis *and* trip frequency. Therefore, predictions about the extent to which anglers adjust their activity levels following a change in fishing conditions were estimated using the multi-stage framework that was described earlier in this paper. The results demonstrate the importance of accounting for the whole impact of management changes to the recreational fishery. For example, a 50% increase in the expected catch rate of Table fish was predicted to increase anglers' demand for trips by 19% and improve the mean value of a fishing trip by $2.37 (Table 5). Together, these changes produced an aggregate annual benefit of $25.5 million per annum[14]. If no allowance was made for the possibility that anglers adjust their fishing activity in response to better catch rates, the gain in consumer surplus only amounted to $5.9 million.

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[13] This participation estimate is based on the following statistics: 1 million people aged 15 years or older reside in the Perth metropolitan area (Aust. Bureau of Statistics 1997); 30% of Perth metropolitan residents are anglers and 75% of these anglers fish from the shore (Aust. Bureau of Statistics 1989); their average fishing frequency is 19 days per year (Reark Research 1997); and 60% of their fishing time is devoted to the Metropolitan and Mandurah regions (Lindner and McLeod 1991).

[14] Assumes that total participation levels by the recreational sector increase by the same proportion as the mean percentage change that was predicted for the sample. This assumption may over-estimate changes in trip frequency because anglers in the sample are likely to be more responsive to changes in fishing conditions than the general angling population.

The other scenario examined was the implementation of a $5 fee for entry to a particular region. Charging an entry fee for access to either of the metropolitan regions dampened anglers' demand for trips by 11-12% and reduced consumer surplus by approximately $2 per trip, or $15 to $17 million across the whole population. Note that the losses in welfare were less than $5 per trip because anglers can avoid the charge by choosing an alternative region where the fee does not apply. As anticipated, charging a fee at Mandurah caused a much lower impact ($3 million loss) than implementing fees at the metropolitan regions.

Table 5: Predicted gains or losses in angler welfare from simulated changes to the fishery. Changes in welfare allow for adjustments in trip frequency made by anglers following a change in fishing conditions.

	Mean change in trip frequency	Mean change in consumer surplus	Aggregated impact on angler population
Simulated change	(%)	($/anger/trip)	($mill/year)
50% increase in CR			
All fish	35%	4.05	47.6
Table fish	19%	2.37	25.5
Bread & Butter fish	9%	1.24	12.1
Non targeted fish	15%	1.94	20.1
Entry fee of $5/trip			
N^{th} metropolitan region	-13%	-1.97	-16.9
S^{th} metropolitan region	-12%	-1.82	-15.6
Mandurah region	-2%	-0.32	-2.7

While the multi-stage model offers a reasonable indication of the net gains and losses from management changes, at least two dimensions of recreational demand were not accounted for. Firstly, both changes were implemented with all other attributes held constant. This could lead to erroneous estimates of welfare impacts because it is conceivable that the benefits from an improvement in catch rate could be eroded if fishing sites became congested as a consequence. Similarly, the losses in consumer surplus from an entry fee may be partly offset by improved catch rates and lower congestion at the site(s) where it is introduced.

Secondly, no allowance was made for the possibility of new entrants. The demand model only predicted the change in activity by existing participants. This is not considered to be a major deficiency of the model because the influx of new participants into the Perth metropolitan fishery following an improvement in catch rates, or other quality attribute, is expected to be small.

Conclusion

At the beginning of the paper it was asserted that government agencies frequently make management decisions with little or no knowledge about the true impact their policies have on the economic well-being of amateur fishers. While management agencies often have a wealth of data about the catch, effort, and expenditure of the recreational sector, they seldom use this data constructively to make inferences about angler preferences and values. This is because methods for analysing recreation demand are rarely understood by managers and are often treated with suspicion. Part of the problem lies with the economics profession who, more often than not, fail to communicate the strengths and limitations of valuation techniques in layman terms.

The other component of the problem stems from the fact that the techniques are still undergoing development and need further refinement before reliable and valid measures of economic surplus can be estimated. This paper has contributed to this refining process by critically evaluating the random utility model and developing an analytical framework for assessing the impact of management changes on angler's welfare.

The paper has extended the current literature on random utility modelling by experimenting with a range of different specifications for catch rate, one of the major attributes of recreational fishing. While other studies have independently used a variety of measures, there has been no single study that has compared different specifications and tested the performance of each model side-by-side. The results of this work showed that the explanatory power of a random utility model can be improved by allowing catch rates to vary over time and by making catch rate specific for each individual in the sample.

Some experiments were also undertaken to examine whether an individual's own perceived level of success at each fishing location is a better predictor of choice than expectations based on actual catch rates. The results do not provide a convincing argument for using perceptions information in future work, especially since the task of collecting pre-trip expectations is difficult. While the survey instrument employed in this study was reasonably successful at eliciting expectations from a voluntary group of avid anglers, it is unlikely that the same degree of success could be met with a random sample of individuals from the angling population. In order to avoid unnecessary survey costs, a sensible course of action would be to firstly examine whether perceptions of quality are indeed different to objective measures. This could be ascertained using a small pre-test or focus group. The findings of this first study could then be used to decide whether a full scale survey of perceptions is warranted.

The future prospects of random utility modelling as a means of valuing recreational benefits appear to be promising, although some hurdles may limit its adoption. In most instances management agencies are unprepared to commission such an analysis on a regular basis because it would be too costly and complex. In addition, there is generally a lack of skilled people available to oversee this type of analysis. Even if economic modelling was undertaken, the resultant models are often difficult to interpret and manipulate without the help of a trained economist.

A number of possibilities should be investigated to overcome these problems. Firstly, the cost of conducting surveys could be reduced if an appropriate method was developed for transferring model results from one fishery to another. The literature on benefit transfer is expanding, but more research is required. Secondly, there is plenty of scope for improving the user interface of simulation models so that decision-makers can experiment with "what if" scenarios. Such an interface has been developed by Adamowicz and Boxall (1997) in their analysis of moose hunting.

Thirdly, a stated preference version of the random utility model known as "choice modelling" may be a more efficient way of eliciting angler preferences. It would overcome the need to conduct a log book survey, thereby reducing the cost of collecting information considerably. Techniques such as choice modelling have the potential to fulfil a wider role beyond just establishing dollar values. As reasoned by Adamowicz and Boxall (1997), the very process of conducting a choice modelling experiment could facilitate greater public involvement in fisheries management. This is because it provides a much more structured approach for gauging people's opinions and preferences relative to the "attitudinal surveys" that are frequently conducted to canvas public opinion about management changes.

The content of this paper has dealt with technical aspects of measuring non-market benefits, but another equally important topic for research relates to social and market institutions. In future it would be desirable to reduce our reliance on analytical tools for revealing values and, instead, develop institutions for signalling information about society's demand for recreation services. For example, certification schemes are an example whereby the institution of a market is used to signal consumers' demand for "environmentally friendly" products. Alternatively, granting recreational fishing clubs with tradeable entitlements for fish and/or spatial access rights have been suggested by Sutinen (1997) as a means of solving allocation problems. In time, it is possible that schemes such as these could be introduced to reveal information about the demand for recreational fishing.

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Appendix

Table A: Poisson estimation results for the objective and perceived catch rate models. The perceptions model was estimated using a truncated Poisson estimator. Values in parenthesis are t statistics.

Dependent variables

Objective model: QT = the number of targeted fish of type *k* caught *per trip* at site or region *j* by individual *i.*

Perceptions model: EQT = the number of fish of type *k* that individual *i* expects to catch *per trip* at site or region *j.*

Regressors	***Objective Model***		***Perceptions Model***	
INPT	0.1410	(1.9)*	0.1634	(2.4)**
ln(THOURS)	0.6273	(25.1)**		
ln(ETHOURS)			0.5382	(18.1)**
STOCK	0.2794	(34.6)**	0.0933	(8.8)**
GEAR	0.53×10^{-4}	(14.0)**	-0.79×10^{-5}	(-1.6)
YEARS	0.0104	(12.6)**	0.1686	(18.9)**
SKILL	0.0323	(1.8)	0.0933	(4.7)**
CLUB	-0.0842	(-1.9)*	0.3977	(8.4)**
MEDIA			0.1291	(4.0)**
Observations	766		742	
L. likelihood	-3917.49		-1936.52	
χ^2 value	2614.22		1225.84	
Pseudo R^2_d	0.3073		0.4287	

The χ^2 value is a statistic used to test the null hypothesis that all coefficients (except the intercept) are equal to zero. For both models, the null hypothesis was rejected at a probability level of 1% which indicates that the models are statistically significant.

The pseudo R^2 reported by LIMDEP is defined below, where λ=predicted Poisson mean and Y=observed value of the dependent variable. The statistic is bounded by 0 and 1. A value of 0.4 approximately equates to a OLS R^2 of 0.8.

$$R_d^2 = 1 - \frac{\sum_{i=1}^{N} Y_i \log(Y_i / \lambda_i)}{\sum_{i=1}^{N} Y_i \log(Y_i / \bar{Y})}$$

Table B: Trip demand functions, estimated using a Poisson model and a Negative Binomial Model.

Dependent variable = TRIPS4, the number of trips made to the study area by individual *i* over the four month survey period.

Regressors	**Poisson Models**		**Negative Binomial Regression**	
INPT	-0.7981	(-2.56**)	-0.9153	(-0.88)
IV_i	0.2949	(8.27**)	0.3063	(2.47*)
$EMPLOY_i$	0.0919	(0.69)	0.0186	(0.05)
$INCOME_i$	-0.0332	(-2.60**)	-0.0081	(-0.20)
$RETIRE_i$	0.6160	(4.43**)	0.6328	(1.67)
$CLUB_i$	-0.7149	(-5.65**)	-0.7946	(-2.53*)
$YEARS_i$	-0.0083	(-2.73**)	-0.0107	(-0.96)
$SHORE_i$	0.9010	(6.08**)	0.8184	(3.03*)
α			0.1132	(3.49**)
Observations	68		68	
L. likelihood	-293.48		-208.68	
χ^2 value	296.21		169.59	
Pseudo R^2_d	0.4753		-	

The over-dispersion parameter in the negative binomial regression (α) was highly significant, which indicates that the negative binomial model is more suitable for the data. Note that the size of coefficients and their signs are very similar to the Poisson models, but fewer of the coefficients are significant. This was not a cause for concern in this study because the predictions made by each model were virtually identical.