Economic values for recreational fishing from the random utility model

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Summary

In many developed countries the focus of fisheries management has widened to include not only the activities of commercial operators, but also those of recreational anglers. As a consequence there is a growing need for information about the preferences, motives, and values of anglers. This information is needed by managers to help formulate policies for conserving stocks and also for reallocating fish stocks between user groups. This paper critically reviews the random utility model as a technique for describing recreation demand, and shows how the model can be incorporated into a framework for simulating the impacts of various policies over time.

Introduction

In many developed countries, recreational fishing now ranks as one of the most popular outdoor leisure pursuits. Surveys frequently reveal that up to 30% of the population go fishing at least once over the course of a year (Grover 1980). In Australia the numbers of recreational fishers have grown to a level where fishery managers are concerned about the adverse impact they might have on stocks of some popular fish species. As a result, counter measures such as bag limits and restricted seasons are being implemented to help prevent over-fishing.

In addition, for fisheries that are jointly used by recreational and commercial fishers, it is becoming increasingly common for managers to introduce policies that intentionally reallocate access to fish stocks from one sector to the other. A good example is the barramundi fishery in the Northern Territory where a buy-back scheme has removed commercial operators from three major river systems, and exclusive access granted to the recreational sector (Macreadie 1993). Other policies that are being used (or being contemplated) for shifting the access of one user group in favour of another include commercial catch quotas, bag limits on recreational catch combined with licensing, closed commercial and/or recreational access to sites, and entry fees to sites for recreational users.

Clearly, the focus of fisheries management has widened to include not only the activities of commercial operators, but also those of recreational anglers. As a consequence there is a growing need for information about the preferences, motives, and values of anglers. This information is needed by managers to help formulate policies for conserving stocks and also for reallocating fish stocks between user groups. Without an understanding of how anglers might respond to various regulations it is difficult to devise effective control measures. Similarly, without measures of economic values for recreational fishing it is difficult to know whether or not reallocation is economically justified.

Research in the field of recreation demand has been very active in the United States, but relatively little work has been done in Australia. The purpose of this paper is to review the random utility model, which is emerging as a favoured technique for analysing the demand for recreational fishing. For background purposes, the paper begins by briefly discussing the traditional travel cost method and its limitations for modelling recreational fishing. This is followed by a detailed look at how the random utility model operates and some of the extensions to the basic model. The last section of the paper suggests how a random utility model could be used to analyse the impacts of resource allocation policies.

Nature of recreational fishing

Relative to commercial fishing, modelling the demand for recreation is quite difficult. There are three main reasons why this is so. Firstly, unlike commercial operators, recreational anglers tend to spread their efforts over a wide range of fish species and sites. The presence of a large number of substitute alternatives makes it difficult to model the demand for any one particular alternative. Secondly, commercial benefits are reasonably easy to quantify as they are a function of total harvest, input costs, and the market price of fish. Recreational benefits, on the other hand, are far less tangible. There is no market for establishing values and catch is not the only factor influencing benefits. A large proportion of benefits are probably derived from intrinsic aspects of the fishing experience.

A third difficulty encountered in developing a model of recreation demand is the lack of information about the recreational sector relative to commercial users. Many fishery management agencies in Australia are beginning to quantify the catch, effort, (and expenditure in some cases) of anglers over time with the use of creel surveys. While this is a start to analysing the physical impacts of recreational fishing, we still have little understanding about the preferences, values, and motives that are driving the behaviour of recreational fishers.

Despite these difficulties, a large number of conceptual and empirical models of recreational fishing appear in the literature. The majority of these studies are based on a common set of principles. That is, the individual must travel to a site in order to consume a recreation "service". Sites within a defined study area are differentiated by their observed level of quality characteristics, such as catch rate and congestion, and measurable costs associated with travelling to the site. Travel costs serve as surrogate prices and observations on the number of visits to each site are used to reveal individuals' preferences for quality attributes of the fishing experience.

Some recent work by Loomis (1995) and Hausman et al. (1995) disaggregate an individual's demand for recreational fishing into four distinct components or choices:

1. Total number of trips to the study area over the course of a year or season (including whether or not to participate at all).
2. Allocation of total trips across sites in the study area.
3. Length of each trip (days).
4. Choice of target species on each trip.

The rationale behind disaggregating demand into these four components is to capture the full effect of reallocation policies or regulations that control angler effort/catch. For example, an increase in the availability of a particular fish species at a distant site (possibly caused by limiting commercial catch) could prompt an angler to swap several short (low cost) trips to nearby sites with one longer (high cost) trip to the more distant site to take advantage of the better prospects of catching fish. This substitution behaviour is likely to significantly influence the size of annual benefits and the amount of recreational effort exerted at each site.

The traditional travel cost method

Background theory

The traditional approach to estimating values for recreational fishing is the simple travel cost method. It focuses mainly on the continuous component of recreation demand, that is the total number of trips taken to a site over the course of a year, and does not explicitly account for an individual's substitution between sites, species, and trip lengths. The method is based on neoclassical demand theory where individuals choose the number of trips that maximise utility subject to a budget constraint. It is assumed that an individual's underlying utility from fishing at a site is a function of the number of visits made to the site, the quality of the site, and the quantity of the numeraire. The simplest version of the method is a single-site model that ignores the presence of substitute sites. The individual solves the following utility maximisation problem:

Max: $u(Z, r, q)$

subject to the budget constraint:

$M = Z + p \cdot r$

where:

Z = the quantity of the numeraire whose price is one,
r = the number of visits to the recreation site,
q = quality attributes of the site (eg. catch rate),
M = exogenous income,
p = cost of a trip to the site.

Maximising the utility equation subject to the budget constraint yields the individual's demand function for visits:

$r = r(p, M, q)$

Empirically, the demand function is obtained by regressing an individual's observed number of visits to the site against the costs incurred in travelling to the site, quality characteristics of the site, income, and other socioeconomic variables.

Two welfare measures are relevant: the value of access to the site and the value of a quality change. The value of access is approximately equivalent to the consumer surplus, or area beneath the demand curve. This is given by the integral of the demand function between the actual cost of a trip and the level of trip costs that corresponds to zero visits. The value of a change in a particular quality attribute is calculated using the coefficient on the quality variable and is given by the difference in consumer surplus before and after the change in quality.

Note that in order to estimate a coefficient for the quality variable, there must be variation in quality across individuals in the sample. This is not possible for a single-site model estimated with cross-sectional data because all individuals visiting the site will experience the same level of quality. For this reason, it is necessary to either use time series data or incorporate data from individuals' visits to multiple sites (see below).

Limitations

The most severe limitation of the traditional travel cost method is its inability to satisfactorily account for the presence of substitute sites. In the single-site model illustrated above, failure to include the travel costs of relevant substitute sites biases the estimated parameters. The researcher is faced with the difficulty of deciding which other sites are substitutes whose prices should be included in the site demand function.

Furthermore, policy makers are usually not interested in knowing the value of just one site. What is more pertinent is the value of changes to quality attributes across multiple sites or the value of changing the number of sites available to individuals in the study area. These questions call for a multi-site model. One common approach is to combine the number of visits made to each site by each individual in the sample and to estimate a single "pooled" demand equation. This is a restrictive simplification because the coefficients on the travel cost and quality variables are constrained to be the same across all sites. Other multi-site models have been proposed but none of them allow substitute prices or substitute qualities to be incorporated in a meaningful way (Bockstael, McConnell et al. 1991).

Another weakness of the travel cost method is the way it handles an individual's choice of time on-site. Simple models assume that the visits made by all individuals to each and every site are of equal length meaning that the opportunity cost of time on-site is the same for every individual. This is clearly an over-simplification of the true situation. If on-site time is allowed to vary between individuals, then the opportunity cost of time on-site should be included in the demand equation. Many studies use the individual's wage rate as a shadow price of time.

More realistic models recognise that on-site time is not only an element of the total cost of a visit, but also provides utility to the individual. For example, McConnell (1992) allows on-site time to be endogenous by including it as a choice variable in the utility function. While this model is an improvement over the simple model, it still makes the unrealistic assumption that individuals choose the *same* amount of time to spend on-site every time they go fishing. As discussed below, the random utility model overcomes this problem by making time on-site a discrete choice which is allowed to vary across sites and trips.

The random utility model

Random utility theory

Random utility modelling is emerging in the literature as the preferred technique for modelling recreational demand because it is able to explicitly describe the substitution behaviour of individuals following a change in access price (travel cost) or quality at one or more sites. Among the first researchers to use this technique was McFadden (1974) who analysed consumers' choice of transport modes. Bockstael et al. (1987) provide an early application of the technique to recreation demand.

With respect to recreational fishing, the method is well suited to analysing an individual's choice of site, length of trip, and target species. These choices are made every time a trip is contemplated and are typically *discrete choices*, as opposed to the annual number of trips which is a *continuous choice* variable and more likely to be planned at the beginning of the season. The random utility model is capable of explaining the probability of discrete alternatives being chosen on each trip, but cannot explain the total number of trips demanded over the season.

The random utility approach is underpinned by the theory of discrete choice which assumes that utility is derived from the attributes of alternatives rather than alternatives *per se* (Hanemann 1984). In order to briefly review the theory, assume that an individual is faced with a choice between a fixed number of fishing sites. The individual's direct utility function is defined as follows:

$$U = U(X_1, \ldots, X_N, q_1, \ldots, q_N, z)$$

Let $X_1, \ldots, X_N$ represent alternative sites, where N is the total number of sites in the individuals choice set. Let $q_1, \ldots, q_N$ represent exogenous quality attributes of the sites. z is the numeraire.

The individual's maximisation problem is to choose (x,z) so as to maximise utility subject to three constraints: (i) a budget constraint; (ii) a constraint that allows the individual to only choose one site at a time and; (iii) a constraint that restricts sites to be "purchased" in fixed quantities. The last two constraints introduce an element of discreteness into the individual's choice.

Next, a conditional indirect utility function is specified which represents the individual's maximum utility that can be gained from choosing site j:

$$U_i = V_i\,(q_j\,,\, M-p_j) \quad j = 1, \ldots, N$$

where income (M) and the cost of a trip to the site (p_j) enter in the form $(M - p_j)$. The individual is then assumed to compare the utility of site j with the utility offered by the best of the remaining sites in the choice set. If the utility from choosing j exceeds the composite alternative, then j is chosen, otherwise it is not. The individual's observed choice can therefore be represented by a set of binary-valued indices denoted by $\delta_1, \ldots, \delta_N$.

Randomness enters the model because the researcher does not know exactly what variables are influencing an individual's utility. This leads to a utility function that is deterministic for the individual, but stochastic from the researcher's viewpoint. An individual's decision rule governing the choice of site *j* is therefore given by:

$$\delta_j(p,q,y,\varepsilon) = \begin{cases} 1 \text{ if } V_j(q_j, M-p_j) + \varepsilon_j >= \max_i V_i(q_i, M-p_i) + \varepsilon_i \text{ all } i \\ 0 \text{ otherwise.} \end{cases}$$

where ε is the error term. Because utility functions for each site are stochastic, decisions about site choice are expressed as probabilities. The probability of site *j* being chosen is given by:

$$\text{Prob(site} = j) = \text{Prob}\{V_j(q_j, M-p_j) + \varepsilon_j > \max_i V_i(q_i, M-p_i) + \varepsilon_i \text{ all } i\}$$

The random utility model is made operational by assuming that the ε's follow independent, identically distributed, extreme value distributions. This assumption yields the multinomial logit model.

$$Prob(site = j) = \frac{e}{\sum_i e} \quad \text{(for all } i \neq j)$$

Parameters of the utility function are obtained by estimating the mulitnomial logit model using maximum likelihood. The likelihood function gives the probability of observing a particular sample of chosen sites, assuming that a logit distribution with as yet unknown parameters of the utility function ($\beta_1, \ldots, \beta_k$) generated the data. The aim of the estimation procedure is to find values of $\beta_1, \ldots, \beta_k$ that make this sample most probable.

Having estimated parameters of the utility function, it is possible to predict how the probability of choosing a particular site will change for each individual in the sample following a change to one or more of the site attributes. This is useful for gaining an insight to how a population of anglers might reallocate their fishing effort after the introduction of management policies that affect quality attributes such as catch rate, or the cost of visiting sites.

Because observed choices are assumed to be a function of an economic model of utility maximisation, it is also possible to calculate the increase in "per trip" benefits for each individual following an improvement in catch rates or some other quality attribute of fishing. The procedures for obtaining welfare measures from discrete choice models are attributable to Hanemann (1985) and to Small and Rosen (1981). Essentially, the value of an improvement is the amount that travel cost must be increased to exactly offset the expected value of the improvement, such that the individual is returned to the same level of utility as before the change. This is a compensating variation measure of welfare. It is also possible to estimate the value an individual obtains from having access to a set of fishing sites and the change in welfare from adding or eliminating a site.

Limitations

The main draw back of the random utility model is that it cannot explain, by itself, an individual's demand for total number of trips over the course of a year. This is because the time horizon of the analysis is based on a single trip rather than a whole season. This is a major problem because improvements in quality at a particular site (or sites) are likely to influence not only an individual's choice of site but also the total number of trips demanded. Without an estimate of how trip demand will be affected, it is not possible to calculate the change in benefits over the entire season. A variety of methods have been employed in the literature to overcome this problem, and are explained under "extensions to the random utility model".

A second limitation of the model is the assumption that individuals' choices are independent across trip occasions. This is likely to be unrealistic, particularly for a sample that comprises multiple observations per individual. It is more reasonable to expect that an individual's choice of site will be influenced by his/her previous experience at each site. Adamowicz (1994) explores the dynamic elements that influence choice by using panel data, and concludes that visitation habits formed by some individuals are likely to have a significant impact on welfare estimates.

Another restrictive assumption of the random utility model implies that the probabilities of choosing site *j* in comparison with site *n* will depend exclusively on the attributes and prices of these alternatives and not on the other available possibilities. This is referred to the independence of irrelevant alternatives (IIA), and is clearly an implausible description of individuals' decision making process. For example, suppose there are three sites to choose from: Lake A, Beach B, and Beach C. An improvement in Beach C is likely to reduce the probability of visiting Beach B relative to the probability of visiting Lake A, a violation of IIA.

The core of the problem is the assumption that the errors associated with the indirect utility function for each alternative are mutually independent. In the example above, the two beaches share all the unobserved characteristics that influence choice of a beach alternative, so this choice set violates the property of IIA. Nested models are commonly used to avoid the problem of IIA (see below).

Extensions to the random utility model

At least three important extensions to the random utility model have evolved in the literature over the past decade or so. These are briefly summarised below:

Nested models

In order to circumvent the IIA problem, a nested random utility model is employed so that choice alternatives which share similar characteristics are bundled into groups. With reference to the example above, individuals are assumed to firstly choose the best "beach" site and the best "lake" site, then choose between going lake fishing or beach fishing based on the respective site utilities.

This nested structure could also be used to model the sequential choices of target species, trip length and site. For example, anglers might first choose to target a particular species then make a joint decision about the site they wish to visit and duration of the trip, conditional on the chosen target species. A number of recreational fishing studies have taken this type of approach (eg. Bockstael, McConnell et al. 1989; Kaoru 1995). Of course, specification of a particular decision sequence should be treated as a maintained hypothesis and alternative nesting structures are likely to influence the size of welfare estimates from quality improvements.

Incorporation of trip de, ınd.

A common method of acco nting for changes in trip frequency following a change in quality attributes is to append a separate model of trip demand to the random utility model. The two models are "linked" by an inclusive value index which is included as a regressor in the trip demand equation. The inclusive value is calculated from the random utility model and represents the net utility of taking a trip, as it captures the value of different sites weighted by their probabilities of being chosen. Changes in quality attributes manifest themselves as changes in the inclusive value which, in turn, generate predictions of new participation levels.

Unfortunately, the inclusive value approach is not entirely consistent with utility theory because site choice decisions and trip demand are not derived using a common utility maximisation framework (Parsons and Kealy 1995). Another weakness of this approach is that the inclusive value increases monotonically with respect to destination quality. This means that all individuals are predicted to increase their participation following a quality improvement. This is an unrealistic description of individual's behaviour as some people might substitute several trips to a close site with one trip to a distant site if catch rates were only increased at the distant site. Some recent studies have avoided this problem by deriving a separate index for expected price and expected quality, using probabilities from the random utility model (Feather, Hellerstein et al. 1995; Parsons and Kealy 1995).

There is a growing body of empirical studies that model recreation demand by combining, and jointly estimating, a multinomial model of site choice with a count data model for total seasonal trips (Terza and Wilson 1990; Yen and Adamowicz 1994; Shaw and Jakus 1996). These models predict the number of trips an individual makes to a particular site over the course of a season, conditional on the total number trips made to all sites in the study area over the same period. Unlike the two-stage demand models described above, parameters in the joint model are estimated simultaneously by maximising a single log likelihood function.

Specification of catch rate variable

Catch rate is a primary variable of interest because it is likely to have a major influence on angler's fishing decisions, and is also of interest to managers who need to devise policies to conserve/allocate fish stocks. Specification of catch rate as a quality attribute in the random utility model is complicated by the fact that it is both a stochastic and endogenous variable. It is stochastic because the angler does not know for certain what his/her catch rate will be before visiting a site. Therefore sites are chosen on the basis of expected catch. Many studies use mean historical catch rates at each site as a proxy for expected catch, thereby imposing the unrealistic restriction that catch be the same for all individuals who visit a particular site. In reality, catch rate is endogenous because individuals have varying levels of experience and can influence catch by using specialised equipment, bait, and varying their length of stay.

Some studies have accounted for the stochastic and endogenous nature of the catch rate variable by combining a household production function with a Poisson process to estimate expected catch rate for each individual in the sample (Smith, Liu et al. 1993; Kaoru, Smith et al. 1995; McConnell, Strand et al. 1995). Catch per trip is assumed to follow a Poisson distribution with mean λ and variance λ. The mean catch per trip for individual i visiting site j (Q_{ij}) is described using a household production function with the following functional form:

$$\lambda = Q_{ij} = \exp(\alpha_0 + \alpha_1 cr_j + \alpha_2 \ln(h_i) + \alpha_3 S_i)$$

where h_i is the hours spent on-site, cr_j is the historic catch rate at the site, and S_i is the angler's skill level measured in years of fishing experience. The advantage of this specification is that catch rate becomes a random variable whose distribution depends upon both characteristics of the individual and an exogenous measure of fish abundance at the site.

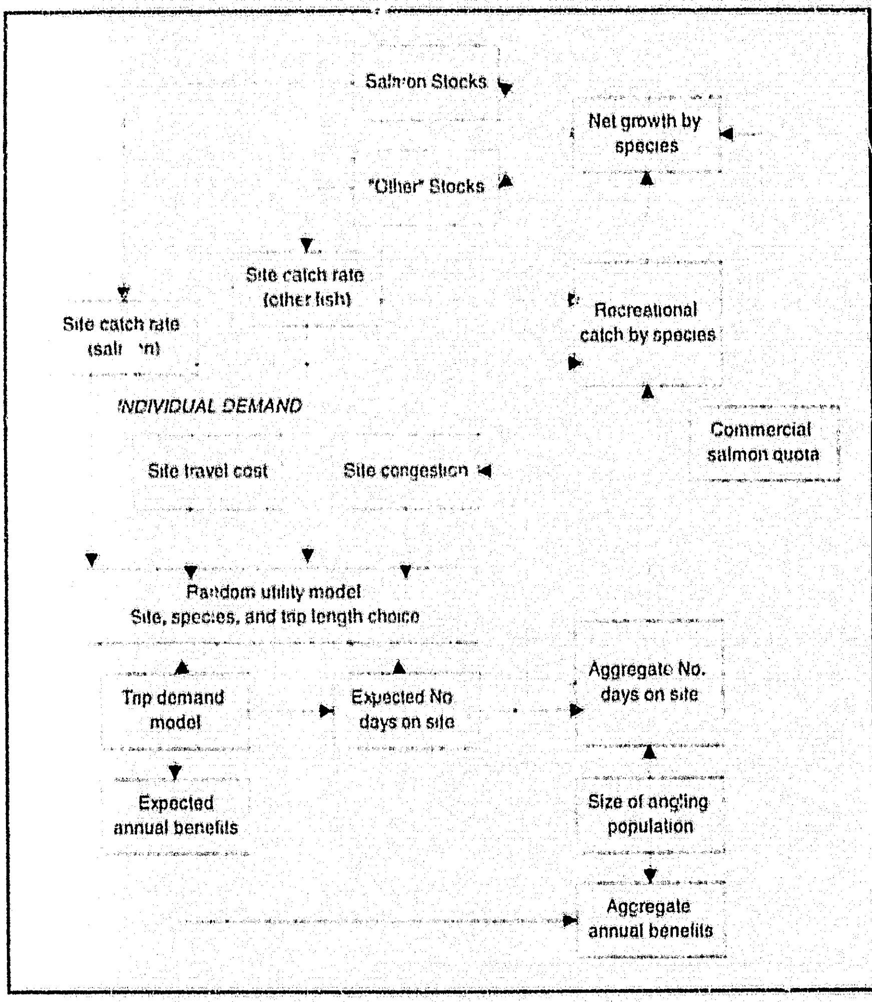
Model of resource allocation

It is reasonably easy to envisage how a random utility model of recreational fishing, combined with a model of trip demand, could be used to analyse the physical and economic impacts of various policies that reallocate access to shared fish stocks. By way of illustration, consider Australian salmon, a species fished both for commercial purposes and for sport. Suppose a management agency is interested in determining how sensitive angler benefits are to changing the availability of Australian salmon, possibly through a quota on commercial catch which partially reallocates stocks to the recreational sector.

Figure 1 depicts a framework for simulating the impacts of such a policy on the recreational sector over time. It shows how changes in key variables (trip frequency, days fished at each site, and annual benefits) are firstly estimated for individual anglers with a behavioural demand model, then aggregated using an exogenous measure of the angling population. Being a dynamic model the aggregate effort in one period influences the level of stocks and congestion in the next period. With an increase in salmon abundance the model might predict that anglers begin to concentrate more of their effort on salmon, consequently choosing to visit sites that offer the highest catch rates for the least cost. The net change in annual benefits will depend upon the change in "per trip" benefits and the total number of trips made by anglers.

An optimal level of quota can be found by varying commercial catch until the combined net present value of recreational and commercial benefits are maximised (for sake of convenience, details of the commercial sector model have been omitted). The same framework could be used to simulate the impact of other policies such as bag limits on recreational catch combined with licensing, closed recreational access to sites, and entry fees to sites for recreational users. The author is currently conducting an empirical study of recreational fishing in Western Australia that uses data from angler logbooks and creel surveys to estimate a random utility model. The model will be used to analyse various policies in the manner described above.

Figure 1: Flow chart of a dynamic simulation model of recreation demand. The chart demonstrates how changes in fish abundance at sites can be linked to changes in participation rates and economic benefits.



Conclusion

Fishery managers tend to maintain a healthy scepticism about the quality and usefulness of benefit estimates that are produced by empirical models of recreational fishing. They are particularly doubtful as to the extent to which these values can be validly compared to commercial values. This paper has shown how improved valuation techniques, such as random utility model, might alleviate these concerns by providing benefit estimates that are supported by collaborative observations of recreational behaviour.

The random utility model has several appealing features. Firstly, it is able to explicitly account for the trade offs that recreational anglers make when choosing a fishing site among a large array of sites that are differentiated by access price and quality. Secondly, the impact of policies that restrict access to sites, affect catch rates, or change the cost of visiting a site, can be readily analysed because demand for fishing is disaggregated at the individual level. Thirdly, welfare measures that are generated by the random utility model are derived from an underlying model of observed individual behaviour. This makes it possible to simulate the magnitude and redistribution of recreational effort across sites that might result from implementation of a particular policy. Output from the random utility model is therefore not only valuable for making judgements about the cost-benefit of reallocation, but is also valuable for identifying effective ways of controlling recreational effort and catch.

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