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Using Choice Experiments to value River and Estuary Health in Tasmania with Individual Preference Heterogeneity

Marit E. Kragt and Jeff Bennett

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About the authors

Marit Kragt is a PhD student in the Crawford School of Economics and Government and the Integrated Catchment Assessment and Management Centre at the Australian National University.

Jeff Bennett is Professor in the Crawford School of Economics and Government at the Australian National University.

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Crawford School of Economics and Government
THE AUSTRALIAN NATIONAL UNIVERSITY

http://www.crawford.anu.edu.au

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Abstract

Choice experiments (CE – otherwise known as Choice Modelling) have become widespread as an approach to environmental valuation in Australia. There are, however, limited applications that have focused on the estimation of estuary values. Furthermore, none of the existing valuation studies have addressed catchment management changes in Tasmania.

The CE study described in this report aims to elicit community preferences for natural resource management options in the George catchment in north-eastern Tasmania. The survey was administered in different sub-sample locations in Tasmania to assess the trade-offs respondents are willing to make between environmental attributes and costs. Catchment health attributes were the length of native riverside vegetation and the number of rare animal and plant species in the George catchment. The area of healthy seagrass beds in the Georges Bay was used as a measure of estuary condition. Results from mixed logit models show that respondents are, on average, willing to pay between \$3.47 and \$5.11 for a km increase in native riverside vegetation and between \$7.10 and \$12.42 per species for the protection of rare native plants and animals, *ceteris paribus*. The results are ambiguous about respondents' preferences for estuary seagrass area. This study further shows significant differences between logit models when accounting for unobserved preference heterogeneity and repeated choices made by the same individual.

1 Introduction

Water resources in Australian catchments are under increasing pressure to satisfy often conflicting environmental and economic goals. Increased agricultural runoff, the introduction of exotic species, point source pollution and habitat destruction have led to concerns over water quality and ecosystem condition in rivers and estuaries. Changes in the catchment environment can have significant economic and social impacts on catchment communities. There is increasing pressure for natural resource managers to incorporate ecological and socio-economic values in decision making processes. However, the information on these different values is limited (Gilmour et al., 2005). To enable an assessment of the various impacts of catchment management, decision makers need scientific data on environmental changes, as well as information on the economic values of catchment environment goods and services.

Choice Experiments (CE), otherwise known as Choice Modelling (CM), have become an increasingly popular stated-preference (SP) approach to valuing environmental changes. CE have been advocated as a flexible and cost-effective technique to estimate the non-market environmental costs and benefits of alternative management strategies (Alpízar et al., 2001, Bennett and Blamey, 2001). In a CE, individuals are given a series of questions (choice sets), where each question shows the outcomes of alternative (hypothetical) policy scenarios. The outcomes are described by different levels of attributes, or characteristics, that depict the good that is being valued. Respondents are asked to choose their preferred option from the array of alternatives. In choosing between alternative options, respondents are expected to make a trade-off between the levels of the attributes. This allows the researcher to observe the relative importance of the different attributes. If a monetary attribute (cost to the respondent) is included in the choice set, the researcher is able to calculate the average individual's marginal willingness-to-pay or *implicit price* for a change in each of the other (non-marketed) attributes: $WTP_a = -\beta_a / \beta_c$, where WTP_a is the willingness-to-pay for attribute a, β_a is the estimated coefficient for that attribute, and β_c is the estimated coefficient for the cost attribute.

CE studies have been undertaken in various Australian catchments to assess the trade-offs between natural resource management and environmental and social impacts. In a CE study by Morrison and Bennett (2004), the benefits of river health improvements were estimated for five New South Wales Rivers (Bega, Clarence, Murrumbidgee, Gwydir and Georges Rivers). Implicit price estimates from nested logit models showed that respondents were WTP between \$1.46 to \$2.33 for a one percent increase in healthy vegetation, between \$2.12 to \$7.23 for a one species increase in native fish populations and between \$0.88 to \$1.92 for a one species increase in waterbirds and other fauna populations. Another application of CEs in an Australian river health context is described in Bennet et al. (2008). This study was aimed at estimating values for a range of attributes of Victorian rivers (Goulburn, Gellibrand and Moorabool rivers). Environmental attributes included percent of pre-settlement fish species and populations; percent of the river's length with healthy vegetation on both banks; and number of native waterbird and animal species with sustainable populations. Results from nested logit models indicated that respondents were WTP between $2.19 to $22.07 for protecting river health, depending on the environmental attributes being valued. Van Bueren and Bennett (2000) used 'waterway health' as one of the attributes in a CE aimed at estimating non-market values associated with land and water degradation in Australia. Waterway health was measured as the total length of waterways healthy enough for fishing and swimming. Results indicated that respondents were, on average, willing to pay $0.08 per household per year for the next 20 years for waterway restoration. To the authors' best knowledge, only two CE studies have aimed to estimate estuary values[1]. A study by Johnston *et al.* (2002a) considered changes in the Peconic Estuary system in the USA. An Australian CE application by Windle and Rolfe (2004) aimed to assess community preferences for the protection of the Fitzroy River estuary, in central Queensland. The estuary attribute was described as the percentage of the river estuary in good condition. Model results indicated that respondents were WTP between $0.50 and $3.89 for a one percent increase in healthy estuary area.

These previous valuation studies indicate that there are significant community values for protecting river catchments in Australia. However, there is limited information about the values of protecting Australian estuaries. Furthermore, none of the existing valuation studies address catchment management changes in Tasmania.

Tasmania is not immune to water quality deterioration and the Tasmanian Government is committed to protecting the State's water resources, while acknowledging possibly conflicting economic, social and environmental objectives (DPIWE 2005). In order to balance natural resource protection with the economic impacts of changed catchment management, and to support efficient decision making, information is needed about the non-market values associated with protecting Tasmanian catchment systems.

The study described in this report is part of EERH project Theme D: 'Valuing Environmental Goods and Services'[2]. This research aims to elicit community preferences for the protection of rivers and estuaries for a case study of the George catchment in north-eastern Tasmania. SP studies that aim to value non-market goods and services are inherently subject to uncertainty

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[1] CE studies in coastal areas are typically aimed wetland valuation or at estimating values associated with marine environments.

[2] This research is a collaboration between the Environmental Economics Research Hub and Landscape Logic, both of which are funded through the Australian Commonwealth Environmental Research Facility.

which can affect both the validity and reliability of value estimates. Validation of methods and results therefore plays an important role when using SP techniques to estimate. A CE survey has been undertaken in different sub-sample locations in Tasmania to assess the trade-offs respondents may make between river and estuary health. River health attributes included the length of native riverside vegetation and the number of rare species in the George catchment. The area of healthy seagrass beds in the Georges Bay was used as an indicator of estuary condition. Model results indicate that Tasmanians hold positive values for the rivers and estuary in the George catchment.

In the next section, the theory of CEs and the econometric models used in this study are explained. Sections three and four describe the case study area and the development of a CE survey for the George catchment. In section five, results of the econometric analyses are presented. The final section concludes.

2 The econometric model

Choice Experiments have their theoretical foundation in random utility theory and in Lancaster's 'characteristics theory of value' (Lancaster 1966). The random utility model describes utility U_{ijt} that individual *i* derives from choice alternative *j* in choice situation *t* as a latent variable that is observed indirectly through the choices people make. Each utility value consists of an observed 'systematic' utility component V_{ijt} and a random unobserved error term ε_{ijt} (Louviere et al. 2000):

$$U_{ijt} = V_{ijt} + \varepsilon_{ijt} = \beta_i ' \mathbf{X}_{ijt} + \varepsilon_{ijt} \qquad j=0,1,...,J;\ t=1,2,...,T \qquad \text{(Equation 1)}$$

The systematic component of utility is assumed to be a linear, additive function of a vector of explanatory variables $\boldsymbol{X_{ijt}}$, which can include the attributes of the alternatives, individual *i*'s socio-economic and behavioural characteristics and features of the choice task itself (Equation 1).

Alternative *j* will be chosen if and only if the utility derived from that option is greater than the utility derived from any other alternative *z* (Equation 2). It is expected that if the quantity or quality of a 'good' attribute in an alternative rises, the probability of choosing that alternative increases, *ceteris paribus*.

$$\Pr(j \mid \mathbf{X}_{ijt}, \varepsilon_{ijt}) = \Pr\{(\beta'_i \mathbf{X}_{ijt} + \varepsilon_{ijt}) > (\beta'_i \mathbf{X}_{izt} + \varepsilon_{izt})\} \qquad \text{(Equation 2)}$$

Different econometric models can be used to estimate parameter vector β_i. It is often assumed that the error terms are independently and identically distributed (IID) Gumbel distributed over alternatives and individuals. This implies that the individual error terms have the following cumulative distribution function (Swait and Louviere 1993):

$$F(\varepsilon_{ijt}) = \exp[-\exp(\mu\varepsilon_{ijt})] \qquad \text{(Equation 3)}$$

where μ is a non-negative scale parameter that impacts variance σ_ε^2 of the error distribution through $\mu = \sqrt{(\pi^2/6\sigma_\varepsilon^2)}$ (Cameron and Trivedi 2005). If it is additionally assumed that β_i does not vary across individuals (that is, $\beta_i = \beta$), the probability that individual i chooses alternative j out of J choice alternatives can be estimated by a *conditional logit* (CL) model[3] specification:

$$\Pr(j|\mathbf{X}_{ijt}, \beta') = \frac{\exp(\mu\beta'\mathbf{X}_{ijt})}{\sum_{j=1}^{J}\exp(\mu\beta'\mathbf{X}_{ijt})} \qquad \text{(Equation 4)}$$

From Equation 4, the estimated parameter values are equal to the true parameters multiplied by the scale parameter. Although this is irrelevant when calculating the probability of choosing alternative j within one data-set[4], it does confound the comparison of parameters between models or data-sets. Simple Wald tests can therefore not be used to compare estimated coefficients across different experiments. Swait and Louviere (1993) propose a procedure for parameter comparisons between data-sets by using the estimated *ratio* of scale parameters.

A consequence of assuming IID Gumbel distributed errors is the Independence of Irrelevant Alternatives (IIA) property, which states that the relative probability of choosing one alternative over another (given that both alternatives have a non-zero probability of choice) is unaffected by the introduction or removal of additional alternatives in the choice set (Louviere et al. 2000). Although the IIA property provides a computationally convenient choice model, it is unlikely to hold if there is unobserved preference heterogeneity amongst respondents (Louviere et al. 2000). In that case, a CL model specification will lead to biased parameter estimates.

More advanced models are available that have less restrictive assumptions than the CL model. Mixed Logit (ML) – also called Random Parameter Logit (RPL)[5] – models are increasingly used to allow for possible error correlation across alternatives and that account for variation in preferences across individuals by specifying random parameters β_i (Equation 5) (Hensher et al. 2005). In a ML model, vector β_i varies among the population with density function $f(\beta_i|\theta)$. These density functions represent the individual taste differences in the population, with $\boldsymbol{\theta}$ a vector of parameters characterising the density function that captures individual deviations from the mean. A distributional form for $\boldsymbol{\theta}$ needs to be specified by the analyst. Commonly

[3] The CL model is appropriate for regressors that vary across alternatives. Some authors incorrectly refer to this model as the multinomial logit model, which is appropriate for alternative-invariant regressors. Any variable that does not vary across alternatives can be included in the CL model by interacting the variable with an ASC (Cameron and Trivedi, 2005: 491-495)
[4] Because all parameters within an estimated model have the same scale parameter
[5] A mixed logit model incorporates a combination of random parameters and latent error components.

used distributions include the normal, lognormal, uniform or triangular distributions (Hensher and Greene 2003; Hensher et al. 2005). Triangular distributions with the standard deviation constrained to equal the mean or lognormal distributions can be used if the analyst wants to restrict the individual parameter estimates to have the same (positive or negative) sign. A drawback of the lognormal distribution is its infinite tail, which can be problematic for WTP estimations. Normal distributions do not constrain the parameter estimates to a specific sign, which may lead to counter-intuitive results, such as a positive coefficient on the cost attribute (Hensher et al. 2005). The introduction of random parameters has the attractive property of inducing correlation across alternatives, thus relaxing the IIA assumption. The random parameter for the kth attribute faced by individual i is:

$$\beta_{ik} = \beta_k + \sigma_k v_{ik} \qquad k = 1, \ldots, K \text{ attributes} \qquad \text{(Equation 5)}$$

where β_k is the unconditional population parameter of the taste distribution; and v_{ik} are the random, unobserved variations in individual preferences that are distributed around the population mean with standard deviation σ_k[6]. Including this standard deviation implicitly accounts for unobserved individual preference heterogeneity in the sampled population (Hensher et al. 2005).

In the ML model the remaining error ε is still IID distributed over alternatives and individuals, such that the *conditional* probability of observing choice j by individual i in choice situation t (conditional on population parameters $\boldsymbol{\beta}'$ and standard deviation $\boldsymbol{\sigma}'$) can be estimated by the familiar logit model:

$$\Pr(j_{it} | \mathbf{X}_{ijt}, \beta_i) = \frac{\exp(\mu\beta_i'\mathbf{X}_{ijt})}{\sum_{j=1}^{J} \exp(\mu\beta_i'\mathbf{X}_{ijt})} \qquad \text{(Equation 6)}$$

As an extension to the ML model, the panel nature of discrete choice data can be exploited using a random-effects model. Panel data models can control for unobserved heterogeneity across the choices made by the same individual, by including an individual specific error term that is correlated across the sequence of choices made by individual i. An added advantage of using a panel data model is to control for omitted and unobserved variables (Campbell 2007). Existing choice experiment studies often fail to fully exploit the panel nature of discrete choice data (Bateman et al. 2008). In a panel data model, the conditional probability of observing a *sequence* of individual choices S_i from the choice sets is the product of the conditional probabilities (Carlsson et al. 2003):

$$S_i(\beta_i) = \prod_t \Pr(j_{it} | \mathbf{X}_{ij}, \beta, \sigma) t \qquad \text{(Equation 7)}$$

[6] Note that we assume a homogeneous, uncorrelated distribution of individual heterogeneity in this specification.

In a typical CE, this sequence of choices is the number of choice questions answered by each respondent. The *unconditional* choice probability is the expected value of the logit probability over the parameter values. This is the integral over all possible values of β_i, weighed by the density of β_i (Hensher et al. 2005):

$$\Pr_i(\mathbf{X}_i, \beta, \sigma) = \int S_i(\beta_i) \cdot f(\beta_i \mid \theta) d\beta_i \qquad \text{(Equation 8)}$$

This model accounts for systematic, but unobserved correlations in an individuals' unobserved utility over repeated choices (Revelt and Train 1998). In the ML panel specification, parameter vector β_i varies between individuals, but is constant across the choice situations for each individual. Because Equation 8 does not have a closed form solution, the model is estimated using simulated maximum likelihood methods (Hensher and Greene 2003).

The panel specification of the model allows for error correlation between choice observations from a given individual. A ML model can further capture error correlation between the *alternatives* in a choice set by specifying additional *error component* terms. These appear as $M \leq J$ additional random effects (Greene and Hensher 2007):

$$U_{ijt} = \beta_i'\mathbf{X}_{ijt} + \varepsilon_{ijt} + c_{jm}\mathbf{W}_{im} \qquad m = 1,...,M \leq J \qquad \text{(Equation 9)}$$

where $\mathbf{W}_{im}$ are normally distributed latent effects with zero mean; and $c_{jm} = 1$ if the random error component appears in the utility function for j. This extension of the model captures additional unobserved heterogeneity that is alternative- rather than individual-specific (Greene and Hensher 2007).

3 The George catchment

Figure 1 Location of the George catchment

The study presented in this report aims to assess the environmental and economic impacts of changed catchment management in the George catchment, in north-east Tasmania (Figure 1). The George catchment is a coastal catchment of about 557 km^2. The total length of rivers in the catchment is approximately 113km, with the main rivers being the Ransom and the North and South George Rivers. The George River flows into Georges Bay estuary (22 km^2) near the town of St Helens. The region is a popular holiday destination, and Georges Bay is intensively used for recreational activities such as boating, swimming, sailing and recreational fishing. The local population is approximately 2,200 (Census 2006). Land use in the upper catchment is a mix of native forestry and forest plantations along with dairy farming, while the lower catchment is used for agriculture and contains most of the rural and urban residences (DPIW 2007). Georges Bay has been extensively developed for oyster farming, with most shellfish farming in Georges Bay is located within Moulting Bay. Approximately 3,000 dozen of oysters were harvested in Georges Bay in 2006 (DEWR 2007).

The quality of the George catchment environment has been identified as an important issue to the local communities (see Rattray 2001; Sprod 2003; and BOD 2007). Concerns about the George catchment condition vary from protection of river water quality and visual appearance of the river to recreational opportunities and water quality in Georges Bay (Table 1). Although the catchment environment is currently in good condition (Davies et al. 2005), forestry practises, agricultural activities and pollution from sewage and urban areas may threaten the health of the George catchment environment (NRM North 2008a and 2008b). Local management actions aimed at preventing natural resource degradation in the George catchment include fencing to limit stock access to rivers, removing weeds along river banks, developing riparian buffer zones, recovery of dairy effluent and improved wastewater treatment.

Table 1 Values identified in the George catchment (Sources: McKenny and Shepherd 1999; Rattray 2001; DPIW 2005)

Catchment value	Specific concerns	
Ecosystem protection	(i)	Maintain existing riparian zones along streams
	(ii)	Maintain good water quality
	(iii)	Improve erosion control (reduced stock access)
	(iv)	Maintain sufficient habitat and flows for rare fish species, birds and Green and Gold tree frogs
	(v)	Protect seagrass areas in Georges Bay
	(vi)	Protect St Helens Wax Flower
	(vii)	Protect modified ecosystems in Georges Bay from which edible fish, shellfish and crustacea are harvested
Consumptive use	(i)	Secure adequate water quality for drinking water supply at St Helens
Recreation	(i)	Protect water quality and quantity for swimming
	(ii)	Maintain and improve angling values
Agricultural water	(i)	Secure water for irrigational usage and stock watering
	(ii)	Provide a fair system of water allocation
Aesthetics	(i)	Maintain a good looking river
	(ii)	Maintain reasonable flows over St Columba falls
	(iii)	Maintain and improve riparian zone quality
	(iv)	Reduce weeds and litter along the rivers
	(v)	Maintain undisturbed status of headwaters

4 Survey development and collection

A CE questionnaire concerning the quality of the George catchment environment was developed in collaboration with local decision makers, natural scientists and community members.

The survey material consisted of an introduction letter, a questionnaire booklet and an information poster. The information poster provided information about the George catchment using maps, photos and charts (Appendix 1). Natural resource management in the George catchment, environmental attributes and attribute levels were also described on the poster. The questionnaire was composed of four sections. An introductory section contained questions on visitation and activities in the George catchment, plus a question on the respondent's perception of current river and estuary quality. The next section explained the choice task at hand, followed by the choice questions. A third section contained questions that aimed to elicit respondents' choice strategies and understanding of the survey. The final section consisted of various socio-economic questions.

An extensive literature review and interviews with experts on river health, threatened species, riparian vegetation and estuary ecology underlied the selection of the attributes included in the choice sets[7]. Important attributes were identified and discussed during four focus group discussions organised in Hobart and St Helens in February 2008, and a further four in Launceston and Hobart in August 2008. Two draft questionnaires were also pretesting during these focus group discussions. The Georges Bay estuary was identified by focus group participants as an important attribute in the George catchment. An explicit estuary attribute was therefore included in the questionnaire. Given that seagrass is often used as an indicator of estuary water quality (see, for example, Crawford 2006; and Scanes et al. 2007), the area of healthy seagrass beds in the Georges Bay was selected as the estuary condition attribute. Other attributes, identified as important by scientists and focus group participants, were included to characterize the condition of the George catchment environment: rare native animal and plant species and native riverside vegetation. A payment attribute was included in each choice set, presented as a one-off levy on rates, to be paid by all Tasmanian households during the year 2009 (Table 2).

The levels of the attributes included in the choice sets reflected the different situations that could occur in the George catchment under alternative catchment management strategies. The levels of the attributes were determined through a combination of literature review, expert interviews, biophysical model predictions and focus group discussions. Attribute levels were identified based on the best available scientific knowledge. The levels of the attributes were

[7] More details about the George catchment questionnaire development are provided in Kragt and Bennett (2008).

defined in a way that was understandable and acceptable to respondents (see Kragt and Bennett 2008b). Each choice set consisted of a no-cost, no new catchment management base alternative, presented as a likely degradation in catchment conditions in the next 20 years. In this scenario, the environmental attributes would fall to their lowest predicted levels. Two alternative options in each choice set presented improvements in natural resource management and resulting protection of the environmental attributes (compared to the base alternative). The attributes and the levels of the attributes are presented in Table 2 and an example of a choice set is shown in Appendix 2.

Table 2 Attributes, attribute description and levels included in the George catchment CE

Attribute	Description	Levels*
Native riverside vegetation	Native riverside vegetation in healthy condition contributes to the natural appearance of a river. It is mostly native species, not weeds. Riverside vegetation is also important for many native animal and plant species, can reduce the risk of erosion and provides shelter for livestock.	40, 56, **74**, 84 (km)
Rare native animal and plant species	Numerous species living in the George catchment rely on good water quality and healthy native vegetation. Several of these species are listed as vulnerable or (critically) endangered. They include the Davies' Wax Flower, Glossy Hovea, Green and Golden Frogs and Freshwater Snails. Current catchment management and deteriorating water quality could mean that some rare native animals and plants would no longer live in the George catchment.	35, 50, 65, **80** (number of species present)
Seagrass area	Seagrass generally grows best in clean, clear, sunlit waters. Seagrass provides habitat for many species of fish, such as leatherjacket and pipefish.	420, 560, **690**, 815 (ha)
Your one-off payment	Taking action to change the way the George catchment is managed would involve higher costs. The money to pay for management changes would come from all the people of Tasmania, including your household, as a one-off levy on rates collected by the Tasmanian Government during the year 2009 The size of the levy would depend on which new management actions are used The money from the levy would go into a special trust fund specifically set up to fund management changes in the George catchment An independent auditor would make sure the money was spent properly	**0**, 30, 60, 200, 400 ($) or[8] **0**, 50, 100, 300, 600 ($)

* Currently observed attribute levels in the George catchment in bold.

[8] One of the split samples in this study included higher payments to test whether choices are impacted by the levels of the cost attribute. The results of these tests will be published elsewhere.

The choice sets were created using efficient design techniques. Efficient design approaches aim to maximise the expected precision of the parameter estimates (Carlsson and Martinsson 2003). A *D-optimal* efficient design aims to minimise the D-error, defined as the determinant of Ω; the asymptotic variance-covariance matrix of a vector of parameters β. To calculate the D-error, some information is required about the expected values of β. Typically, *prior* values of β can be elicited from survey pretests. These prior estimates may not give a precise estimate of the final βs. A *Bayesian* design strategy can account for the uncertainty in the prior parameter estimates (Scarpa and Rose 2008). This simply involves including the distribution over β (π_β) into the calculation of the efficiency criterion:

$$\min E_\beta[\{\det(\Omega(\beta, \mathbf{X}_{tj}))\}^{1/K}] = \int_{\Gamma^K} \{\det(\Omega(\beta, \mathbf{X}_{tj}))\}^{1/K} \pi_\beta d\beta \qquad \text{(Equation 10)}$$

where β is the parameter vector, $\boldsymbol{X}$ is a matrix of attribute levels in t = 1,2,…,T choice sets, with j = 1,2,…J alternatives in each choice set; K is the number of parameters to be estimated and Γ is the number of draws from the assumed distribution over the parameter estimates π_β. Prior information on the expected values of the parameters β was elicited from the results of a survey pretested during the August focus groups. A total of 24 choice sets were generated using a Bayesian *D*-efficient design technique. Some combinations in the choice set design were not feasible, for example because one alternative completely dominated the others in the levels of the environmental attributes but not in costs. These combinations were removed from the choice design, leaving a total of 20 choice sets to be included in the questionnaire. The total number of choice sets was divided into four blocks, so that each respondent was presented with five choice questions.

In order to achieve a representative sample of Tasmanian households, but within the practical limits of this study, the survey sample was restricted to the two largest population centres in Tasmania (Hobart and Launceston) and the local community around the town of St Helens. Each location was divided into multiple smaller local sampling units, stratified to cover the complete sample location and a range of community types. A random sample was taken from these areas, using a 'drop off/pick up' method[9] with the assistance of local service clubs. Surveyors received a training session and detailed instructions on the sampling locations and procedures. The questionnaires were collected in November 2008 and March 2009.

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[9] This method involved surveyors to visit randomly selected households within each stratified sampling unit with the request for survey participation. When the householder agreed to participate, a copy of the questionnaire was left behind and arrangements were made to pick up the completed survey booklet at a convenient time

5 Results

A total of 1,432 surveys was distributed, of which 933 (65.2%) were returned. There were significant differences in response rates between Launceston and the St Helens and Hobart sub-samples (Table 3). An important constraint experienced by surveyors was respondents' reluctance to participate in the survey. It became clear that respondents suspected political motives behind the survey, notwithstanding extensive efforts to stress the unbiased and scientific nature of the study. The local community was particular reluctant, leading to difficulties in collecting a sufficient number of surveys for further analysis (Table 3). All information presented was based on scientific data and had been discussed in several focus groups. Nevertheless, respondents' feedback indicated strong disparities between perceived catchment conditions and the current conditions of the George catchment as described in the survey. Particular concerns were raised about the impacts of forestry activities in the catchment. Given the limited number of useable surveys in St Helens and Hobart, no valid conclusion could be inferred about differences in values across populations. A second wave of sampling will be conducted in February 2009 to increase the sample size.

Respondents who consistently chose the base alternative because they protested against paying a government levy were not included in the analysis. This resulted in a total of 832 surveys (Table 3). Because not all respondents answered all the questions, the total number of choice observations available for analysis was 3,898.

Table 3 Number of available surveys by location

Location	Respondents (#)	Response rate (%)
St Helens	109	50.6
Launceston	346	81.5
Hobart	377	59.1
Total	**832**	

In Table 4, the descriptive statistics of the sample used in the estimations are presented. A series of χ^2-test were conducted against the Tasmanian population statistics (ABS 2007). These showed that, although mean income, educate and age in the sample were not significantly different from the State average, the distribution of the socio-demographic variables was significantly different across sub-samples. Care should therefore be taken when interpreting the conclusions of this study as population values.

To account for possible differences in responses between local and urban respondents, a dummy variable 'urban' (one for the Launceston and Hobart subsamples) was included in the analysis. To account for the oversampling of highly educated respondents, a dummy variable for 'university education' was included in the analysis. About 37 percent of the urban sample had a university degree (over 13 years of schooling), whereas about 23 percent of the local sample had a university degree.[10]

A proportion of respondent did not disclose their income (15.7 percent). There were no differences in the percentage of respondents who did not report their income between sample locations. To avoid loosing observations, the missing observations on income were recoded to their location means. A dummy variable 'noinc' was included in the analysis to account for possible differences between those respondents who did not disclose their income and those who did.

Two attitudinal variables were also considered in the questionnaire: level of agreement with the survey information and level of confusion caused by the choice questions. These variables were measured as respondents' agreement with the statements "I agreed with the information presented on the poster" and "I found answering questions 4 to 8 confusing". Both statements were measured on a 5-point Likert scale where 1 = strongly disagree and 5 = strongly agree. Of the 801 respondents who answered the attitudinal questions, the majority (strongly) agreed with the information (468), whereas 43 respondents (strongly) disagreed. About 29 percent of respondents were (strongly) confused by the choice task (230 respondents). To account for the impacts of these attitudinal characteristics, agreement and confusion were included in the model specification.

Table 4 Descriptive statistics of George catchment survey sample*

Variable		Mean	Std	Median	Min	Max
Visitation	Number of visits to the George catchment in the past 5 years	5.29	7.93	2.5	0	25
Age	Respondent age (yrs)	45.67	14.76	45	18	91
Income	Annual household income ('000 $, before taxes)	74.94	43.84	67.6	7.5	210
Gender	=1 if the respondent is male	0.40	0.49	0	0	1
Education	Respondent education (yrs)	13.39	2.21	13	8	18
Uni	=1 if the respondent has at least one year of university training	0.38	0.49	0	0	1
Urban	=1 if the respondent is from Launceston or Hobart	0.87	0.34	1	0	1
Envorg	=1 if the respondent is a member of some environmental organisation	0.09	0.28	0	0	1
Noinc	=1 if the respondent did not disclose income	0.16	0.36	0	0	1
Agree**	Agreement with poster information	3.59	0.74	4	1	5
Confuse**	Confusion by the choice task	2.81	1.02	3	1	5

* Based on available observations. ** Measured on a 5-point Likert scale where 1 = strongly disagree and 5 = strongly agree.

[10] Compared to 18 and six percent for the urban and local population average respectively (ABS, 2008).

Limdep 9.0 was used to fit conditional logit and mixed logit models, of which the final conditional logit, and two mixed logit specifications are presented in Table 5. A Hausman test showed that the IIA property was violated in a CL model, therefore additional ML models were estimated. To capture the possibility of error correlations between the 'new management' alternatives a common error component was included for the two new-management alternatives (Campbell et al. 2008). The ML models were estimated by simulated maximum likelihood using Halton draws with 500 replications (Train 2000). The CL and ML1 models threat each choice as a separate (cross-sectional) observation, whereas the panel specification in the ML2 model accounts for possible error correlation between choices made by the same individual. Given that each individual answered five choice questions, the ML2 model is a more appropriate model specification for analysing CE data.

In all models, an alternative specific constant (ASC) was specified for the base alternative to test whether respondents have a systematic tendency to choose the no-cost, no new catchment management base alternative over the new-management alternatives that can not be explained by observed variables. Socio-economic variables were interacted with the ASC to avoid singularity of the matrix. Respondent's age and additional variables such as sample location, household size and association with the farming of forestry community were not significant in the models and are not included in the final model specifications[11]. For the ML specifications, all the choice attributes were initially included as random parameters to account for variation in respondents' preferences towards the attributes. Several random parameter distributions were tested. Following Greene *et al.* (2006), a constrained triangular distribution was used for the random cost parameter, to ensure a negative sign on each individual's cost parameter. It was not desirable to constrain the distributions on the environmental attributes, as respondents may have positive or negative preferences towards the attributes. A normal distribution was therefore defined for the environmental attributes.

The estimated coefficients all have the expected signs. Cost of new management is negative and significant in all models, whereas an increase in species is positive and significant. Seagrass and riverside vegetation are not significant at the 5% level in the cross-sectional CL and ML1 models. But when we account for error correlations between individual choices in the ML2 model, the parameter estimates on the seagrass and vegetation attributes are positive and significant. The significant standard deviations for the random parameters reveal individual preference heterogeneity across choices for all attributes, except for the variation in the seagrass parameter distribution in the ML1 model.

[11] Results of these models are not reported here but are available upon request from the authors.

Table 5 Conditional and mixed logit model results

	CL		ML1 (cross-section)		ML2 (panel)	
Variable	Parameter	S.E.	Parameter	S.E.	Parameter	S.E.
Random parameter means						
Costs ($)	-0.003^{***}	0.000	-0.005^{***}	0.000	-0.010^{***}	0.000
Rare species (#)	0.033^{***}	0.002	0.047^{***}	0.005	0.087^{***}	0.006
Seagrass (ha)	0.000	0.000	0.000	0.000	0.001^{**}	0.000
Vegetation (km)	0.002	0.003	0.007^{*}	0.004	0.037^{***}	0.005
Random parameter standard deviations						
Cost			0.005^{***}	0.000	0.010^{***}	0.000
Rare species			0.045^{***}	0.007	0.090^{***}	0.007
Seagrass			0.000	0.013	0.004^{***}	0.001
Vegetation			0.032^{***}	0.010	0.057^{***}	0.006
Non-random parameters						
ASC (=1 for 'new management')	-1.882^{***}	0.503	-2.247^{***}	0.709	-2.914	1.817
Income	0.006^{***}	0.002	0.009^{***}	0.002	0.014^{***}	0.005
No-reported-income	-0.432^{***}	0.127	-0.605^{***}	0.194	-0.726^{*}	0.441
Visitation	0.043^{***}	0.014	0.056^{***}	0.021	0.091^{*}	0.055
Env-org	2.072^{***}	0.381	2.490^{***}	0.545	2.617^{*}	1.019
Age	0.001	0.003	0.003	0.004	0.004	0.011
Urban	0.556^{*}	0.335	0.778	0.502	1.397	1.307
Uni-degree	0.340^{***}	0.114	0.481^{***}	0.178	0.690	0.431
Agree	0.595^{***}	0.072	0.799^{***}	0.156	1.045^{***}	0.276
Confuse	-0.250^{***}	0.051	-0.369^{***}	0.083	-0.556^{***}	0.186
Latent error component (std)			0.746	1.014	2.573^{***}	0.286
Log-likelihood	-3455.7		-3436.93		-2800.05	
Adjusted - $\rho^{2\ (a)}$	0.190		0.193		0.342	
AIC	6939.29		6909.85		5636.10	
BIC	7027.05		7022.68		5748.93	

Note: ***, **, * = significance at 1%, 5% and 10% level. $^{(a)}$ Adjusted to the number of parameters, against an equal market share model with LL=-4282.39

The ASC parameter is negative and significant in the CL and ML1 models, indicating that respondents generally prefer the 'no-cost no-new-management' option over one of the environmental management alternatives, *ceteris paribus*. This bias towards the 'no-cost' option is consistent with results from other studies (Louviere et al., 2000). However, this tendency is not significant in the ML2 model. The coefficients on income, visitation, and membership of an environmental organisation were positive and significant in all models, indicating that higher incomes, more visits to the region and membership of an environmental organisation are associated with a higher probability of choice for the new-action alternatives. Note that the 'no reported income' variable was negative and significant. This shows that - on average - respondents who refused to reveal their income are also more likely to choose the 'no-action' option. Respondent's age is not significant in any of the model specifications, and preferences are not significantly different between urban and local respondents in the ML model specifications. More than 13 years of education is not significant in the ML2 panel model specification, which means that having a university degree does not affect the probability of choosing one of the change alternatives over the no-new-actions option. A consistent result across all models is that respondents who indicated that they agreed with the survey information are more likely to choose for new environmental management, and that respondents who were confused by the choice sets are more likely to choose the no-action option.

The ML models include an additional error term to capture unobserved error correlation between the two new-management alternatives. The error component is significantly different from zero in the ML2 model indicating heterogeneity across the utilities that respondents derive from the new-management alternatives. Comparing the log-likelihoods and the adjusted ρ^2 goodness-of-fit measures between models, the ML models provide a better model fit than a CL model. Furthermore, the ML2 model that accounts for error correlation between choices made by the same respondent explains a larger proportion of the choice variation in the data and is the preferred model for this data-set.

Table 6 Marginal willingness to pay ($) for environmental attributes (95% confidence interval in parentheses)

Attributes	CL model		ML1 model		ML2 model	
Seagrass (ha)	-0.106	(-0.26 - 0.05)	0.00	(-0.13 - 0.12	0.108^{***}	(0.02 - 0.19)
Riverside vegetation (km)	0.682	(-1.00 - 2.36)	1.535^{**}	(0.001 - 3.09)	3.573^{***}	(2.52 - 4.61)
Rare species (#)	10.95^{***}	(9.03 - 13.2)	10.06^{***}	(8.01 - 12.09)	8.417^{***}	(7.23 - 9.61)

Note: ***, **, * = significance at 1%, 5% and 10% level. 95% confidence intervals based on the 2.5th and 97.5th percentile of the simulated WTP distribution.

The estimated average marginal WTP for a change in each of the attributes in the George catchment survey are presented in Table 6. The 95% confidence intervals were calculated using parametric bootstrapping from the unconditional parameters estimates using 1,000 replications (Krinsky and Robb 1986). Results from the ML2 model show that respondents are, on average, willing to pay $0.11 for a hectare increase in seagrass area, $3.57 for a kilometre increase in native riverside vegetation and $8.42 for the protection of each rare native animal and plant species, compared to the base level, *ceteris paribus.*

A formal test for equality in WTP estimates is the non-parametric convolutions approach proposed by Poe *et al.* (1994; and 1997). This test involves simulating confidence intervals for the *differences* between the marginal WTP estimates. A one-sided significance level can then be calculated as the proportion of negative values in the distribution of differences. A bootstrapping procedure with 1,000 draws was used to calculate the WTP difference between the ML2 and CL models and between the ML2 and ML1 models. The results are reported in

Table 7. The equivalence between the marginal WTP estimates of the CL versus ML2 models is rejected for all the environmental attributes. When comparing the ML1 and ML2 models, the Poe *et al* test shows less pronounced differences between estimates of marginal WTP for seagrass and the rare species attribute, but still shows that a significant difference in WTP estimates for riverside vegetation between models.

Table 7 Testing the equivalence between WTP estimates

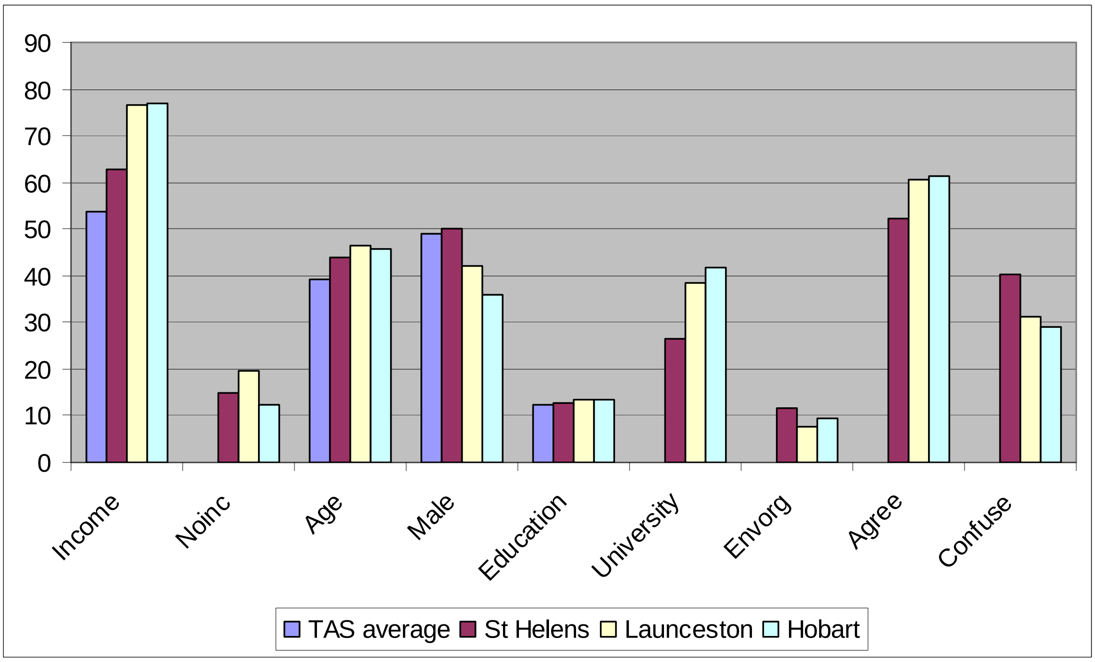
	CL vs ML2		ML1 vs ML2	
Attribute	90% confidence interval	p-value	90% confidence interval	p-value
Seagrass	(0.35 0.07)	0.007	(0.24 -0.02)	0.071
Vegetation	(4.58 1.18)	0.001	(3.62 0.50)	0.014
Species	(4.67 0.59)	0.010	(3.56 -0.38)	0.086

6 Results by location

From a policy perspective, and for more accurate extrapolation of the survey results to the population, it is useful to assess whether differences exist between preferences of within-catchment and out-of-catchment respondents. The utility respondents derive from the George catchment environment may differ across the populations in St. Helens, Hobart and Launceston. Further models were therefore estimated on the separate data-sets of the three sub-sample locations. For completeness, the main socio-economic descriptors from Table 4 are reported by location in Figure 2. Mean income, the proportion of women and education are significantly lower in the St. Helens sub-sample than in the urban sub-samples.[12] There are also statistically significant differences between the Hobart and St. Helens sub-samples in the proportion of people who were confused by the choice task (p-value = 0.025) and between the Hobart and Launceston sub-samples for no-reported-income (p-value = 0.007).

[12] p-values of 0.002, 0.014 and 0.000 compared to the urban samples respectively.

Figure 2 Descriptive statistics by location



Note: Mean annual gross household income (‘000 $), mean age (yrs), mean education (yrs), no-reported-income, male, university and membership of an environmental organisation as percentage of total, agree as percentage of respondents who agree or strongly agreed and confuse as percentage of respondents who were confused or highly confused.

Given the panel character of the data-set, a mixed logit panel specification was considered the more appropriate model specification for analysing the choice data and was used to analyse the different subsets of data by location. The same variables as used in the complete sample model specifications were initially used to analyse the sub-sample data. However, in the separate location models, not all covariates were significant.[13] Only the models with significant variables for at least one of the three location split samples are therefore reported in Table 8.

[13] Results for the all-variable models by location are available upon request from the authors.

Table 8 Mixed logit panel model results and WTP by sample location

	St. Helens			Launceston			Hobart		
Variable	Parameter	S.E.		Parameter	S.E.		Parameter	S.E.	
Random parameter means									
Costs ($)	- 0.009***	0.002		- 0.010***	0.001		- 0.011***	0.001	
Rare species (#)	0.117***	0.019		0.084***	0.008		0.077***	0.008	
Seagrass (ha)	0.001	0.001		0.001	0.001		0.001*	0.001	
Vegetation (km)	0.048***	0.016		0.034***	0.008		0.037***	0.008	
Random parameter standard deviations									
Cost	0.009***	0.002		0.010***	0.001		0.011***	0.001	
Rare species	0.082***	0.021		0.085***	0.009		0.070***	0.010	
Seagrass	0.004	0.002		0.002*	0.001		0.005***	0.001	
Vegetation	0.053***	0.016		0.048***	0.010		0.056***	0.009	
Latent error component (std)	5.393***	1.757		2.850***	0.531		4.204***	0.532	
Non-random parameters									
ASC (=1 for 'new management')	4.869	8.126		- 2.412	2.073		- 4.116*	2.449	
Income	0.034	0.030		0.017**	0.008		0.000	0.009	
No-reported-income	1.521	2.603		- 0.981	0.696		- 1.411*	0.811	
Visitation	- 0.065	0.184		0.052	0.077		0.554***	0.208	
Uni-degree	6.134	4.226		1.595**	0.679		- 0.143	0.777	
Agree	0.046	1.431		1.035**	0.446		2.671***	0.624	
Confuse	- 1.172	0.983		- 0.207	0.295		- 0.963***	0.366	
Log-likelihood	-356.90			-1191.32			-1264.19		
n	531			1624			1744		
Adjusted - $\rho^{2\ (a)}$	0.363			0.328			0.346		
WTP-seagrass [(b)]	0.12	(-0.15	0.39)	0.08*	(-0.04	0.22)	0.12**	(-0.0	0.24)
WTP-vegetation [(b)]	5.11***	(1.72	8.59)	3.58***	(1.93	5.21)	3.47***	(2.04	4.88)
WTP-rare species [(b)]	12.42***	(8.29	16.6)	8.78***	(7.01	10.6)	7.10***	(5.60	8.62)

Note: ***, **, * = significance at 1%, 5% and 10% level; [(a)] against an equal market share model; [(b)] 95% confidence intervals between parentheses based on the 2.5th and 97.5th percentile of the simulated WTP distribution.

The signs on the choice attribute parameters are the same across locations and conform to *a priori* expectations. Cost is negative and significant in all sample locations, while vegetation and rare species are positive and significant. The standard deviations in the choice attribute random parameters are also significant across sample locations, indicating significant heterogeneity in respondents' preferences towards the attributes. The error component is significant in all samples, which means there are significant differences in the error variances of the 'new management' attributes compared to the no-cost base alternative. Note that the general insignificance of the seagrass random parameter estimates indicates that respondent's utility is not affected by the changes in seagrass area used in the survey. There is significant heterogeneity in preferences towards seagrass beds in the Georges Bay, particularly in the Hobart sample.

When estimating ML models on the separate sample locations, only a few of the socio-economic variables were significant in explaining choice probabilities. None of the variables were significant in the St. Helens sample, which implies that the choices of local respondents can be explained predominantly by the choice attributes. Respondents with higher incomes, a university degree and who agreed with the survey information were more likely to choose for 'new management' options in the Launceston sample, *ceteris paribus*, while respondents who visited the George catchment more often, who agreed with the survey information and were not confused by the choice task were more likely to choose for 'new management' options in the Hobart sample. Hence different socio-demographic characteristics are important in explaining choices across locations.

Table 8 also reports the implicit prices, or marginal WTP estimates, for each of the environmental attributes used in the George catchment CE. These were calculated using parametric bootstrapping from the mean parameter estimates with 1,000 replications. The WTP for seagrass is not significant in the St. Helens sample, and significant at the 10% and 5% level respectively in the Launceston and Hobart samples. Using the Poe *et al.* (Poe et al. 1994) convolutions approach, the WTP for seagrass is statistically equal across locations. The WTP for an increase in healthy riverside vegetation ranges from \$3.47/km in Hobart to \$5.11/km in St. Helens. The differences in WTP for riverside vegetation are also not statistically significant across locations. The WTP estimates for the protection of rare species are significantly different[14], with local respondents being prepared to pay significantly more per species than out-of-catchment respondents.

7 Discussion and further research

The experiment described in this report was aimed at eliciting the values that Tasmanian households hold for protecting natural resources in the George catchment. Several difficulties were encountered while administering the survey in Tasmania. Respondents were concerned about results being used for political purposes (by 'forestry' or 'green' interests). In the local community, the study generated a strong reaction, possibly because the scientific information did not match local perceptions of catchment condition.

The results from this study show that Tasmanians hold, in general, positive values for protecting native riverside vegetation and rare native animal and plants species in the George catchment. These results are in line with previous studies on mainland Australia (see, for example, Morrison and Bennett 2004; and Bennett et al. 2008). A direct comparison between the WTP estimates of different studies is difficult, as every study is contextual and studies

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[14] $p = 0.05$, 0.011 and 0.085 for a comparison between St. Helens and Launceston, St. Helens and Hobart and Hobart and Launceston respectively.

tend to use disparate measurement units for the attributes. It can therefore not be concluded that Tasmanians hold higher or lower values for catchment protection than households on mainland Australia households. The George catchment is, like many Tasmanian catchments, in a relatively pristine condition. Future empirical work will be required to reveal whether values estimates from the George catchment survey can be transferred to other catchments in Tasmania or Australia.

There is limited information on the non-market values that may be impacted by changes in estuary water quality. This study therefore included changes in seagrass area - often used by decision makers as an indicator of estuary water quality - to measure estuary values. The different results for seagrass area between models and location are noteworthy. The willingness-to-pay for healthy seagrass beds in the Georges Bay was insignificant in the local sample, while it ranged between $0.08 and $0.12 per hectare in the urban samples. These results show that seagrass in itself may not be a valuable attribute, particularly for the local population. Feedback from respondents indicated that seagrass beds are sometimes perceived as a hindrance to recreational activities. This contends the usefulness of seagrass as an indicator of estuary values and warrants further research on how to describe and measure estuary quality.

Different model specifications reveal significant preference heterogeneity amongst respondents for costs, riverside vegetation and rare species. Furthermore, it is shown that accounting for correlated errors between choices made by the same individual leads to a significantly better model and different value estimates. The evidence presented in this report strongly suggests that future Australian catchment valuation studies should take individual heterogeneity and the panel nature of choice data into account.

The research described in this report is ongoing. Further research will be directed at analysing different survey split samples to test for differences between socio-demographic groups (for example, gender bias) and survey versions (see Kragt and Bennett 2008a). Possible sources of heteroskedasticity in the random parameters and correlation between random parameters will be explored. It is also proposed to include respondents' choice strategies in the analysis of the data, as this is expected to provide further insights into respondents' value preferences.

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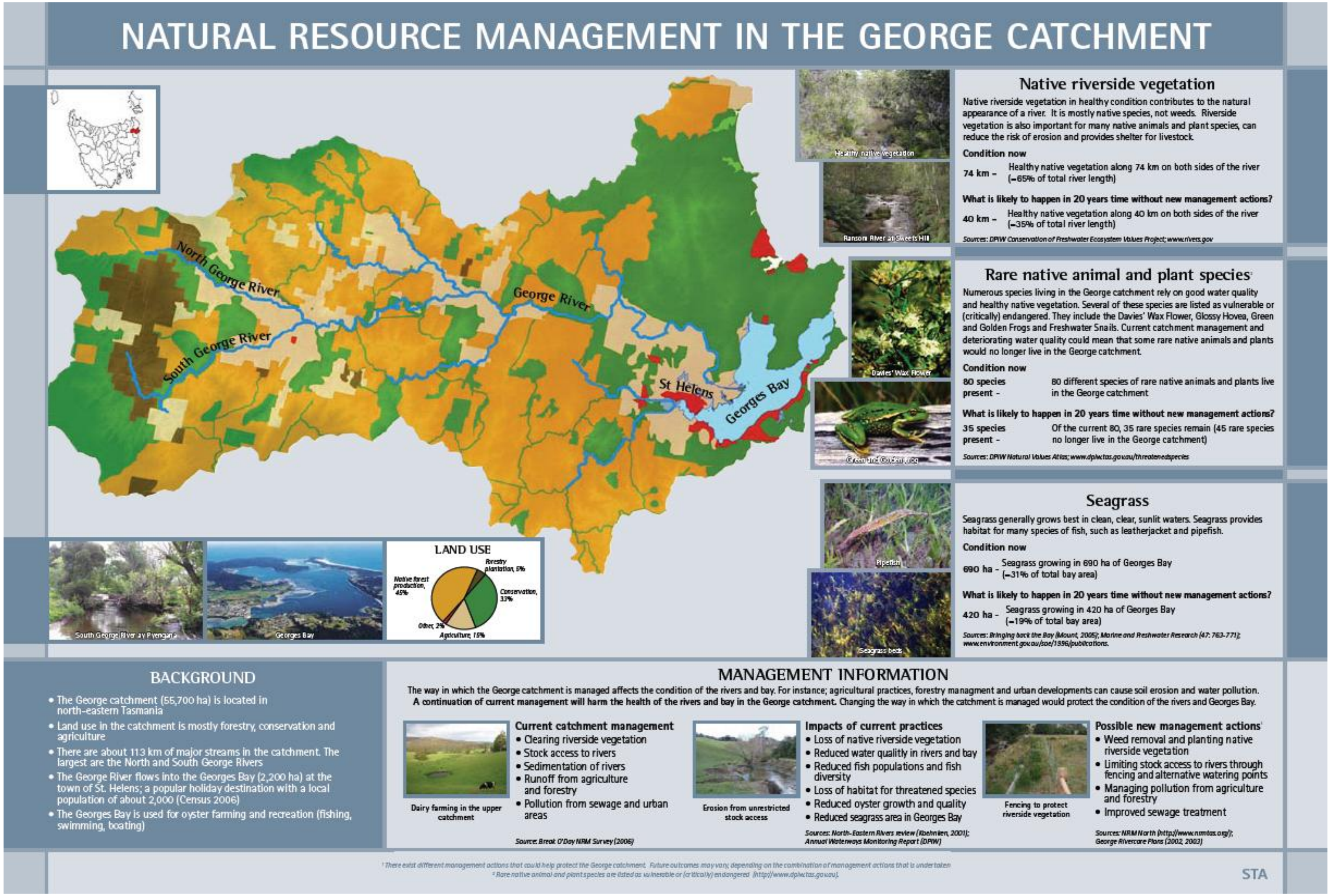
Appendix 1 Information poster included in the George catchment CE



Appendix 2 Example choice set

Question 4

Consider each of the following three options for managing the George catchment.
Suppose options A, B and C are the **only ones** available.
Which of these options would you choose?

Features	Your one-off payment	Seagrass area	Native riverside vegetation	Rare native animal and plant species	YOUR CHOICE
Condition now		690 ha (31% of total bay area)	74 km (65% of total river length)	80 rare species live in the George catchment	
Condition in 20 years					Please tick **one** box
OPTION A	$0	420 ha (19%)	40 km (35%)	35 rare species present (45 no longer live in the catchment)	☐
OPTION B	$60	815 ha (37%)	81 km (70%)	50 rare species present (30 no longer live in the catchment)	☐
OPTION C	$30	690 ha (31%)	74 km (65%)	65 rare species present (15 no longer live in the catchment)	☐