Estimating the Value of Ecosystem Services in New Zealand Pastoral Farming – A Choice Modelling Approach

Ramesh Baskaran [a], Ross Cullen [a], Steve Wratten [b]

[a] Commerce Division, Lincoln University, Canterbury, New Zealand,
baskarar@lincoln.ac.nz

[a] Commerce Division, Lincoln University, Canterbury, New Zealand,
cullenr@lincoln.ac.nz

[b] National Centre for Advanced Bio-Protection Technologies, Lincoln University, Canterbury, New Zealand,
wrattens@lincoln.ac.nz

Abstract

There is growing concern in New Zealand about agricultural intensification particularly over the environmental impacts of pastoral farming on selected ecosystem services (ES) such as air quality, ground and surface water quality and availability, and landscape quality. Non-market valuation techniques have been used recently to estimate values of marginal changes in some of these ES. This paper presents an application of the Choice Modelling method to obtain monetary estimates such as willingness-to-pay (WTP) for improvements in the levels of these selected ES. Policy implications are explored by calculating Compensating surplus (CS) for a number of alternative management scenarios. The overall welfare estimation results show that respondents expect positive marginal utility for improvements in these selected ES and are willing to pay more for higher levels of environmental enhancement.

Key Words: ecosystem services, pastoral farming, choice modeling, willingness-to-pay

JEL Classification: Q1, Q2, Q5

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1.0 Introduction

The New Zealand economy relies heavily on export income from pastoral farming. International competition means that New Zealand farmers face pressure to farm more intensely to maintain their position as low cost producers. Present pastoral farming trends show that the sector is growing and becoming more intensive in its use of several inputs including fertiliser, energy, water for irrigation, capital to produce more output from the same area of land (PCE 2004). However, increases in the amount and intensity of pastoral farming have adverse harmful environmental effects such as increased nitrate leaching to streams and rivers, increased methane gas emissions, increased demands for surface and groundwater for irrigation and reduced variety in pastoral landscapes (PCE 2004). These effects of increased intense pastoral farming reduce the ability of pastoral land to provide some important Ecosystem Services (ES) such as clean water and air.

This paper estimate values for improvement in selected environmental attributes that are linked to intense pastoral farming. As the values attached to improvement in environmental attributes reflect individual's marginal utilities, the estimations allow us to quantify the social benefits of the changes. The paper also studies respondents' level of awareness of the environmental degradation caused by pastoral farming and the trade-off between economic growth and improvement in ES associated with pastoral farming.

As government policies tend to focus on greenhouse gas emissions from livestock, water quality, water use and scenic views of pastoral farms, the study may provide policy-makers with much needed information on the economic value of these ES. Thus, policies can be introduced to influence sustainable pastoral farming practices. The paper also contributes in terms of applying advanced non-market valuation modelling, namely the choice modelling (CM) technique, where the application of valuation studies to ES is very limited.

The paper is organised as follows: The next section describes the background of the study and environmental degradation caused by farming activities. Section 3 describes the CM method using different model specifications. This is followed by Data Collection Section where CM design of experiment and logistic are explained in detail.

Section 5 reports the results and discussion of different models. The main objective of this paper is the estimation of respondents' WTP for improvements in selected ES as presented in Section 6 and subsequently in Section 7, the compensating surpluses for aggregate changes as policy implications are outlined. The paper concludes in Section 8 with the overall findings of the study.

2.0 Background

The agricultural sector in New Zealand currently contributes 52 percent of the value of exports and 10 percent of GDP. Its GDP contribution is expected to rise from \$7.6 billion at March 2006 to \$8.7 billion by March 2008 (MAF, 2007). Dairying is the largest industry in New Zealand, accounting for 20 percent of export income. Total sheep numbers were estimated at 40.1 million at 30 June 2006, up 219,000 on the 2005 figure (SNZ, 2007). The number of dairy cattle at 30 June 2006 was estimated at 5.2 million, up 1.6 percent from 2005. At 30 June 2006, the number of beef cattle (4.4 million) was the same as the previous year. The total deer number was estimated at 1.6 million in 2006. The deer farming industry has developed in the past 25 years, from just 109,000 deer in 1981.

However, there is increasing concern over environmental damage caused by intensification of pastoral farming in New Zealand. The intensive farming systems have affected the delivery of key ES such as clean air and water, the creation and maintenance of fertile soils, pollination, gas regulation, and processes to decompose and assimilate waste. These ES have immense social and economic value, and damage to some of these services may be irreversible. Often, these services are not measured or valued and taken into account in resource allocation decisions. Consequently, unsustainable agriculture practices can lead to severe environmental degradation.

Nutrients such as nitrogen from fertilisers are frequently found in streams, rivers, and lakes. Growth of algae caused by nutrient loading is a common problem. It lowers water clarity and quality and reduces fish numbers. Excess amounts of animal waste spread on agricultural land are also sources of nitrate leaching to waterways and sometimes cause serious problems of faecal contamination in rivers and streams. Usage of nitrogen fertiliser has doubled on pastoral farming and has increased by 25 per cent in the sheep and beef sectors between 1991 and 2002 (PCE, 2004). Fertiliser usage and amount of animal waste are expected to continue increasing in pastoral farming and to have increasing impacts on water quality. For example, as nitrogen applications increase from 0 to 200 kg N/ha on an average Waikato dairy farm, nitrates leached increased from 15 to 31 kg N/ha (PCE, 2004).

New Zealand's agricultural greenhouse gas emissions have grown by 1 percent per year since 1990, and are predicted to continue to grow at this rate over the medium term (MAF, 2007). Globally, 14 percent of greenhouse gas emissions come from agriculture. In comparison, 49 percent of New Zealand's greenhouse gas emissions come from the agricultural sector. The emissions consist of methane from livestock, and nitrous oxide from animal waste and nitrogen fertiliser use (MAF, 2007). Pastoral farming contributes 99% of New Zealand's total methane emissions due to the growth in the number and average weight of livestock (O'Hara *et al*., 2003). The average methane emission (CO_2 equivalents) per pastoral hectare per year is 1.98 tonnes (MED, 2006).

Irrigation can increase the reliability of farming systems and deliver higher levels of productivity and profit to pastoral farms. However, use of water for irrigation can impact flows of rivers, reduce groundwater levels and harm wetlands. Extraction of water for pastoral farming can sometimes lead to water shortages and to destruction of aquatic ecosystems. Water use for irrigation on pastoral land is 1500 million m^3/year (SNZ, 2004).

Pastoral scenery is a major part of the NZ landscape. Some pastoral landscapes contain only pasture, livestock, post and wire fences, but no trees or hedges. Tait and Cullen (2006) noted that the area of shelter belts in Te Pirita region of Canterbury has reduced during the last two decades as a result of dairy conversion. For instance, a 46% or 6.7 metres per hectare loss of shelter belts was measured between 1984 and 2004.

3.0 Method

Assumptions about respondents' behaviour are introduced into random utility demand theory through specification of a utility function. The utility function measures the level of satisfaction an individual experiences as a result of consuming particular goods and services. The CM approach refers to survey-based methods that rely on information about households' WTP for an improvement in service quality, or about their choices and behavioural changes in hypothetical scenarios involving a quality change. The theoretical basis of CM is the random utility model (RUM) developed by McFadden (1974). Under the RUM framework, the utility function for each respondent can be expressed as:

$$U_{ij} = V_{ij} + \varepsilon_{ij}, \tag{1}$$

where U_{ij} is an individual i's true but unobservable utility of choosing alternative j, V_{ij} is the observable systematic component of utility (indirect utility function) and ε_{ij} is an error term that represents unobservable (to the researcher) influences on individual choice. RUM assumes that the individual acts rationally and chooses the alternative with the highest level of utility (i.e., utility maximizer). As the researcher cannot observe the individual's true utility function, a probabilistic utility function is used in the estimation. Assuming that the individual can choose alternative option j in the choice set to any alternative option k, then the probability that alternative j is chosen is given by

$$P_j = \Pr ob(U_j > U_k) = \Pr ob(V_j + \varepsilon_j > V_k + \varepsilon_k) = \Pr ob(V_j - V_k > \varepsilon_k - \varepsilon_j) \forall k \in C$$

where C is the set of all possible alternatives. It is apparent that the higher the probability for choosing an alternative, the larger the difference in observed utility. In other words, the probability of choosing alternative j increases as the difference in estimated utility between the two alternatives increases. In order to derive an explicit expression for these probabilities, an assumption is made about the distribution of the error terms which determine different models such as Multinomial Logit (MNL), Nested Logit (NL), and Mixed Logit (ML).

Assuming that each of the error terms is Type I Extreme Value distributed and the difference between error terms is logistically distributed, the probability that a respondent chooses alternative *j* is given by:

$$P_{ij} = \frac{e^{\mu V_{ij}}}{\sum_{k \in C} e^{\mu V_{ik}}} \tag{2}$$

This formulation is known as the conditional logit model (McFadden, 1974) or presently, multinomial logit model (McFadden, 2001) where μ is a scale parameter, inversely proportional to the standard deviation of the error distribution, and typically assumed to be one[1].

The individual indirect utility function (V_{ij}) can be modelled in different ways of specification. The simplest functional form which only includes attributes from the choice sets is an additive structure:

$$V_{ij} = ASC_j + \sum_k \beta_k X_{ijk} \tag{3}$$

where *ASC* is an alternative specific constant for alternative *j*, β_k is a vector of coefficients associated with the *k*th attribute, and *X* are attributes from the choice sets. The ASC is known as constant. It takes up any unobserved variation that cannot be explained by either the attributes or the socio-economic variables such as tastes. There are $J - 1$ ASCs in the choice set where *J* is the number of alternatives. In order to extract more information, an advanced functional form is to include socio-economic as well as attitudinal variables into the utility functions by estimating the variables interactively, either with the ASC or with any of the attributes from a choice set:

$$V_{ij} = ASC_j + \sum_k \beta_k X_{ijk} + \sum_m \omega_m ASC_j * S_{mi} + \sum_n \delta_n X_{ijk} * X_{ijk} \tag{4}$$

[1] Earlier the MNL expected utilities are modeled in terms of characteristics of individuals and then later McFadden (1974) proposed modeling the expected utilities in terms of characteristics of alternatives. Now, the MNL expected utilities are modeled on individual characteristics as well as the attributes of the choices or combination of both.

where ω_m is the vector of coefficients representing interaction between ASC_j and the mth socio-economic characteristics of individual i (S_{mi}); and δ_n is the coefficient vectors of interaction between attributes in the choice set C composed by J alternatives.

An important implication of this model is the assumption of independence of irrelevant alternatives (IIA)[2]. This implies that for each individual, the ratio of the choice probabilities of any two alternatives is independent of the utility of any other alternatives. In other words, an option being chosen should be unaffected by the inclusion or omission of other alternatives. This can lead to unrealistic estimates of individual behaviour when alternatives are added to or deleted from the choice set. This condition is normally tested using the test derived by Hausman and McFadden (1984). Violation of IIA may occur if close substitutes are included in the choice sets or there are heterogeneous preferences among respondents (Morrison *et al*., 1998). If a violation of the IIA assumption is observed, then more complex models of choice are required such as NL (for correlated alternatives) and ML (for heterogeneity preferences).

In this paper, it is likely that the IIA assumption may be violated for two reasons. Firstly, the choice alternatives of improved management are structured in such a way as close substitutes. For example, Alternative 1 and 2 are considered to be improved environmental management plan, and adding Alternative 2 can be seen as a close substitute for Alternative 1. If there is unobserved correlation among the alternatives, the model will generate inconsistent parameter estimates because error terms are no longer independent but correlated across those alternatives. One way of solving this problem is to cluster the related alternatives (Alternative 1 and 2) into a subgroup where the error terms of alternatives within a nest are correlated with each other, and the error terms of alternatives in different nests (Alternative 3) are uncorrelated. Hence, a two level nested choice model is structured as shown in Figure 1.

[2] The IIA assumption is identical to the assumption of Independent and Identically Distributed (IID) random components of each alternative.

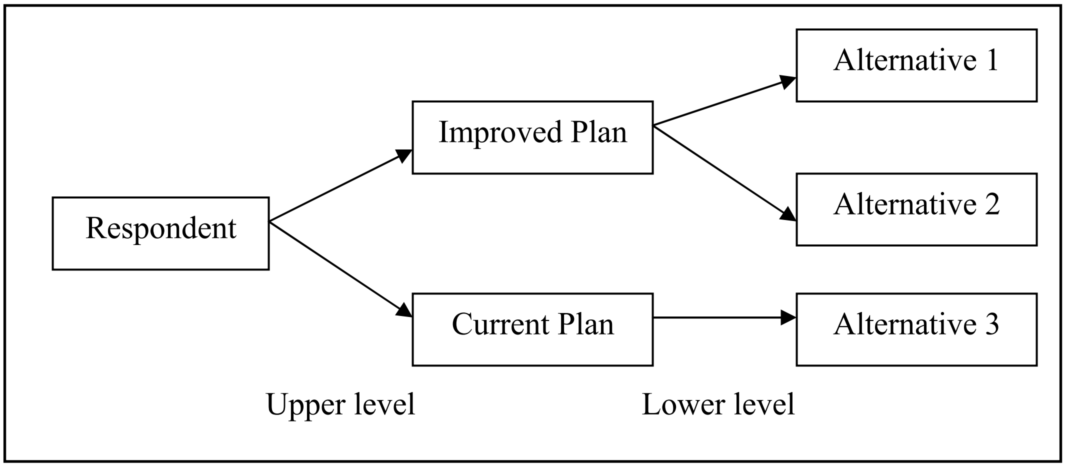

Figure 1: The choice making decision for the NL model

The utility associated with upper level (between improved plan and current plan) is assumed to be explained by ASC (equal to 1 for Alternative 1 and 2 and 0 otherwise) and the interactions of socio-demographics characteristics of the respondents and alternatives characteristics (ASC). Choices at the lower level (between Alternative 1 and Alternative 2) are explained by the ASC1 (equal to 1 for Alternative 1 and 0 otherwise), levels of the attributes, and interaction between attributes. The following are the utility equations for the NL model of this study:

Upper level

$$V_{ij}(\text{Im}\,proved) = ASC + \sum_m \omega_m ASC * S_{mi}$$

$$V_{ij}(Current) = \sum_m \omega_m ASC * S_{mi}$$

Lower level

$$V_{ij}(Alternative1) = ASC1 + \sum_k \beta_k X_{ijk} + \sum_n \delta_n X_{ijk} * X_{ijk}$$

$$V_{ij}(Alternative2) = \sum_k \beta_k X_{ijk} + \sum_n \delta_n X_{ijk} * X_{ijk}$$

$$V_{ij}(Alternative3) = \left(\sum_k \beta_k X_{ijk} + \sum_n \delta_n X_{ijk} * X_{ijk} \right) \equiv 0$$

Thus, in a two-level NL model, the probability of an individual *i* choosing the *j*th alternative in nest *r* (P_{jr}) which is in lower level is represented as:

$$P_{ijr} = P_i(j \setminus r)P_i(r) \tag{5}$$

where $P_i(j\backslash r)$ is the probability of the individual *i* choosing the *j*th alternative conditional on choosing the *r*th nest of outcome, and $P_i(r)$ is the probability that the individual *i* chooses the *r*th nest (upper level). Applying Kling and Thomson (1996) formulation:

$$P_i(j \setminus r) = \frac{e^{V_{ijr}/\lambda_r}}{e^{I_r}} \tag{6}$$

$$P_i(r) = \frac{e^{\lambda_r I_r}}{\sum_{k=1}^{R} e^{\lambda_k I_k}} \tag{7}$$

where:

$$I_r = \log\left[\sum_{q=1}^{J_r} e^{V_{iqr}/\lambda_r}\right] \tag{8}$$

is referred to as the *inclusive value* (IV) or *expected maximum utility*, λ_r is the coefficient of the IV which measures the degree of substitution between the various nests, *R* is the number of nests, and J_r is the number of alternatives in nest *r*. In order to be consistent with utility maximization, λ_r must lie between zero and one (McFadden, 1981). There has been a number of NL model applications to estimate the value of environmental good and services in the literature recently (Blamey *et al*., 2000; Bennett *et al*., 2004; Othman *et al*., 2004; Windle and Rolfe, 2005; Morgas *et al*., 2006).

The other potential reason of IIA violation in this paper is the assumption of homogeneous preferences among the respondents for both MNL and NL models. This is an unrealistic behavioural assumption because each respondent may have different perception/unobserved characteristics that may influence his or her choice making decision. For example, respondents with higher education and income who live in the urban area (same observed characteristics) may support the environmental improvement plans. Each individual places their own particular weight on their choice making, which leads to correlation across the utility of alternatives for each individual and again leads individuals to violate the IIA assumptions. In order to incorporate taste variation amongst the respondents, a ML (also known as Random Parameter Logit) model will be considered. Furthermore, the ML model assumes no IIA property.

The ML model have some advantages over MNL and NL as it provides the analyst with valuable information regarding the interpretation of the unobserved part of utility, and provides unbiased parameter estimates even incorporating unobserved heterogeneity in the data (Train, 1998; Train, 2003; Hensher *et al*., 2006; Hanley *et al*., 2006; Wang *et al*., 2006). The utility function for ML model is generally described by:

$$
\begin{aligned}
V_{ij} &= ASC_j + \sum_k \beta_{ki} X_{ijk} + \sum_m \omega_m ASC_j * S_{mi} + \sum_n \delta_n X_{ijk} * X_{ijk} \\
V_{ij} &= ASC_j + \sum_k X_{ijk}\left(\beta_k + \eta_{ki}\right) + \sum_m \omega_m ASC_j * S_{mi} + \sum_n \delta_n X_{ijk} * X_{ijk} \\
V_{ij} &= ASC_j + \sum_k \beta_k X_{ijk} + \sum_k \eta_{ki} X_{ijk} + \sum_m \omega_m ASC_j * S_{mi} + \sum_n \delta_n X_{ijk} * X_{ijk}
\end{aligned}
$$

In contrast to previous models, ML model assumes β_{ki} to vary among respondents, hence letting $\beta_{ki}=\beta_k+\eta_{ki}$ where β_k is the mean of the coefficient and η_{ki} is a vector of random term that captures non-observable individual's tastes relative to the average taste given by the $\beta_k s$ [3]. In the MNL model, η_{ki} are identically zero, implying no correlation in utility across alternatives. Here, with nonzero error components, η_{ki} , utility become correlated across alternatives, hence relaxed the IIA assumption. It is important to note that in this paper, the ML model assumes to treat the coefficients as varying over respondents but being constant (independent) over choice situations for each respondent. The coefficient vector β_{ki} varies in the population with density $f\ (\beta \backslash \theta)$, where θ is a vector of actual parameters of the taste distribution. The purpose of the ML model is to estimate the

[3] The MNL and NL models assume the β_k as fixed parameter allowing a single β_k representing the entire sample population. Whereas in the ML model, the β_k is treated as a random parameter allowing for respondents within the sampled population to have different β_k.

population parameters θ (mean and standard deviation of tastes in the population) that best describe the distribution of individual parameters. Assuming that ε_{ij} is identically and independently distributed extreme value Type 1, the unconditional choice probability that respondent *i* will choose alternative *j* thus becomes

$$P_{ij}(\theta) = \int L_{ij}(\beta) f(\beta \setminus \theta) d(\beta)$$

where $$L_{ij}(\beta) = \frac{e^{V_{ij}(\beta)}}{\sum_n e^{V_{in}(\beta)}}$$

is the logit probability evaluated at parameters β. Since the analyst does not observe the true tastes, the probability becomes the integral of $L_{ij}(\beta)$ over all possible values of β, weighted by the density of β. Since the integral has no closed form, the parameters are estimated through simulation by maximizing the log-likelihood function. This is done by pooling random draws for each β_{ki} (each respondent parameter) from population density, $f(\beta\backslash\theta)$, and calculating the logit probability, $L_{ij}(\beta)$, for each draw and then averaging it. As a result, it provides an unbiased estimator of P_{ij}. Prior to estimating the model, it is also necessary to assume how the β_k coefficients are distributed over the population. The most common distributional functional forms are normal, lognormal, uniform and triangular (Hensher *et al*., 2005).

The results of the CM estimation can be used to estimate two types of WTP values: marginal WTP or Implicit prices; and Compensating Surplus (CS) or mean WTP. Marginal WTP are the marginal rates of substitution (MRS) between the non-marketed attributes and the monetary attribute. The MRS is derived as the partial differentiation of the attribute of interest with respect to utility. Hence, in a model without any socioeconomic interactions with the attributes, they are estimated as the ratio of the coefficient of non-monetary attribute and the coefficient of the monetary attribute (β_m):

$$\text{Marginal WTP} = -\left(\frac{\beta_{non-monetary}}{\beta_{monetary}}\right)$$

CS is the appropriate estimate of the WTP for a change from the current situation[4]. The WTP for a change from the current situation to improved situation relies on other factors incorporated in ASCs, socioeconomic and attitudinal variables on why respondents might (or might not) want to choose a plan. CS estimates are calculated using Hanemann (1984) utility difference expression:

$$CS = -\frac{1}{\beta_m}\left\{\ln\left[\sum_{j=1}^{J} e^{V_j^1}\right] - \ln\left[\sum_{j=1}^{J} e^{V_j^0}\right]\right\}$$

where β_m is the parameter estimate on cost (payment vehicle), V^0 represents the utility of the current management plan (before the change) and V^1 represents the level of utility of the improved management plan (after the change) in a given J number of alternatives in each state. The above CS equation is feasible to measure welfare changes for MNL and ML models. As for the NL model, the CS is calculated using the following specification (Kling and Thomson, 1996):

$$CS = -\frac{1}{\beta}\left\{\ln\left[\sum_{r=1}^{R}\left(\sum_{j=1}^{J_r} e^{V_{rj}^1/\lambda_r}\right)^{\lambda_r}\right] - \ln\left[\sum_{r=1}^{R}\left(\sum_{j=1}^{J_r} e^{V_{rj}^0/\lambda_r}\right)^{\lambda_r}\right]\right\}$$

It is important to note that the above CS estimation is the mean WTP per respondent of the sample (average over individuals in the sample). In order to calculate the CS for population, the mean WTP value should be aggregated to determine the WTP of the wider community to achieve management changes.

4.0 Data Collection

The choice modelling surveys were designed to contain multiple choice questions (choice situations) about alternative policies for improving four ES attributes on pastoral farms. The questionnaire consisted of three parts. The first part contained questions regarding respondents' opinions and their awareness of current environmental degradation situation caused by pastoral farming. These questions had the objective of

[4] The CS is calculated based on Hicksian surplus. Here, it is assumed that the $\beta_{\text{monetary attribute}}$ equals the marginal utility of income. Since it is assumed to be constant then the Hicksian surplus and the Marshallian surplus (also known as the consumer surplus) are equivalent (Small and Rosen, 1981).

introducing the respondent to the subject of ES services. The second part of the survey contained the choice situation questions. Before that, respondents were briefed about the four attributes of ES and associated cost to the household. The cost to the household (the payment vehicle) was defined as an additional annual payment to the regional council responsible for the management of the environment over the next five years.

In the choice questions, respondent were asked to select an option they favoured the most out of the three alternatives provided. Each option contains the four attributes and the cost to the household with various levels of attribute combinations. Attributes discussed were methane gas emissions, nitrate leaching to water, water usage for irrigation, and scenic views of pastoral farms. Each attribute was presented to respondents as several discrete levels. For example, the attribute of methane gas emissions from pastoral farms was presented as having three discrete levels: 30% reduction from current emission level; 10% reduction from current level; and 'no change' from current emission level. The payment vehicle is loss of household income. All of the attributes selected are factors that a policy maker can affect, directly or indirectly, and they were regarded as relevant based on the information from literature. A sample choice situation question is shown in Figure 2 with the relevant attribute names, levels, and the options. The last part of the survey contained questions regarding the respondents' socio-economic background.

As there are three levels for the methane gas emission, nitrate leaching, and water attributes, two levels in the scenic view attribute, and four levels in the cost to household, there are 3^3 x 2 x 4 factorial designs (Louvier *et al*., 2000). For statistically efficient choice designs, a D-efficient fractional factorial designs excluding unrealistic cases was adapted to each of the choice questions (Huber and Zwerina, 1996; Terawaki *et al*., 2003). This was performed with linear D-optimal using SAS statistical software (Kuhfeld, 2001). The programme created 72 choice sets which were then allocated to 12 versions (survey) of 6 choice sets, 8 versions of 9 choice sets, and 6 versions of 12 choice sets. Hence there were 26 versions of the survey questionnaire differing only in the attribute levels in the choice questions. Each choice question has three alternatives and the third alternative was always a status quo (current level). In other words, each respondent in each choice set has to choose either improved environmental management (Alternative 1 or 2) or the current situation (Alternative 3).

	Option A	Option B	Option C
Methane emissions	10% reduction	30% reduction	No change
Nitrate Leaching	30% reduction	30% reduction	No change
Water Use for Irrigation	10% reduction	10% reduction	No change
Scenic Views	No change	30% more trees, hedges, plantations	No change
Loss of your household income ($ per year for the next 5 years)	$60	$60	$0

Option A ☐ Option B ☐ Option C ☐

Figure 2 Example of a choice set from the New Zealand Pastoral Farming and the Environment questionnaire

A mail survey form was selected for data collection. In the beginning of November 2005, pilot surveys were tested on students at Lincoln University and on randomly selected residents in both the South and North Island. During late November and early December 2005 a pre-survey card, survey booklet and cover letter, and a reminder post-survey card were sent to 2080 respondents selected from the NZ electoral roll using a random stratified sampling design. The sample was divided into two strata: 1040 respondents were randomly selected from the Canterbury region (which contains the largest area of pastoral farming in NZ) and 1040 from the rest of NZ. The study received a total of 391 and 370 responses with completed questionnaires out of each total region mailed survey questionnaires. The overall total effective response rate was 37%. As a result, a sample size of 702 respondents was used in the data analysis.

5.0 Results and Discussion

The choice data were analysed using LIMDEP 8.0/NLOGIT 3.0 statistical software. The sub-samples of 6, 9 and 12 choice sets data were pooled into one dataset. The study preferred to use effects coding instead of dummy coding. The advantage of using effects coding is that the effect of all attributes levels are estimated and are uncorrelated with the intercept (Adamowicz *et al*., 1994; Louviere *et al*., 2000; Hensher *et al*., 2005; Bech and Gyrd-Hansen, 2005). Table 1 provides a more complete description of all explanatory variables and their specified effects coding based on the levels.

Two different MNL models were estimated initially as base models. The first is a basic model that shows the importance of the choice set attributes in explaining respondents' choices across the three different alternatives. The second model includes interactions between socio-demographic variables and ASC. As expected *a priori*, respondents have, in general, a preference for lower payments, fewer gas emissions, better water quality and availability, and a landscape with more trees coverage. A Hausman and McFadden (1984) test was performed for both models in order to check the validity of the IIA assumption. Results show that the MNL models suffer from violations of the IIA assumption at the 1% significance level. As a result, biased parameter estimates and consequently, will lead to inaccurate welfare estimation. Therefore, the MNL model is inappropriate for estimation of this data.

Table 1 Variables used in the choice models

Variable	Description
Attribute variable	
ME10	10% reduction in Methane gas emissions from the current level Effect Coding: 1 if 10% reduction; 0 if 30% reduction; -1 if no change
ME30	30% reduction in Methane gas emissions from the current level Effect Coding: 1 if 30% reduction; 0 if 10% reduction; -1 if no change
NL10	10% reduction in Nitrate leaching to waterways from the current level Effect Coding: 1 if 10% reduction; 0 if 30% reduction; -1 if no change
NL30	30% reduction in Nitrate leaching to waterways from the current level Effect Coding: 1 if 30% reduction; 0 if 10% reduction; -1 if no change
WU10	10% reduction in water use for irrigation form the current level Effect Coding: 1 if 10% reduction; 0 if 30% reduction; -1 if no change
WU30	30% reduction in water use for irrigation form the current level Effect Coding: 1 if 30% reduction; 0 if 10% reduction; -1 if no change
SV	30% more in scenic views (i.e. trees, plantations) on pastoral farms Effect Coding: 1 if 30% more variety; -1 if no change
COST	Loss of household income during the next 5 years - NZ$0, 30, 60, 100
ASC	Alternative-specific constant taking on a value of 1 for options 1 and 2 in the choice sets, and 0 for the base option (current level)
ASC1	Alternative-specific constant used in NL model taking on a value of 1 for option 1 in the choice sets, and 0 for the base option (option 2)
Non-attribute variable	
AGE	Age of respondent (in years)
EDU	Education levels
INCO	Income of household before tax
RURAL	Dummy variable taking on a value of 1 for respondents living in rural areas, and 0 otherwise
INCOST	Interaction between income and cost

In order to avoid the IIA problem, a two level NL model was estimated and the results are shown in Table 2. The coefficients for all of the attributes in the utility functions are significant and all have the *a priori* expected signs. In other words, respondents prefer those pastoral farming management scenarios, which results in higher levels of reductions in methane, nitrate leaching, water usage and more scenic view in relative to current levels. Interestingly, the WU30 attribute which was found to be insignificant in the MNL models, is positively significant at 10% level. This implies that respondents have a positive utility impact from a 30% reduction in irrigation water usage. However, the ASC1 (for choosing options 1 or 2) variable was found to be insignificant as the respondents perceived there is no systematic difference between these alternatives as both are improved management plans relative to current plan. In addition, the ASC (for choosing improved plans or current plan) in the branch choice indicates a negative sign and is significant at the 5% level. This means that in the NL model, respondents are not that keen on improving the ES attributes which is in contrast to MNL model. This may be due to framing effects where respondents may have understood the choices in a different context than what is expected by the researcher (Bennett and Rolfe, 2001).

Table 2 Nested Logit (NL) model results

Variable	Coefficients	Standard errors
Utility functions		
ASC1	-0.03832	0.0553
ME10	0.13594***	0.0341
ME30	0.30536***	0.0317
NL10	0.18288***	0.0316
NL30	0.55806***	0.0312
WU10	0.18218***	0.0337
WU30	0.05446*	0.0286
SV	0.27203***	0.0236
COST	-0.00989***	0.0013
Branch choice equations		
ASC	-0.53277**	0.2219
ASCAGE	-0.00686***	0.0025
ASCEDU	0.23689***	0.0263
ASCINCO	0.03859**	0.0172
ASCRURAL	-0.71388***	0.0788

Inclusive value parameters		
Improved	0.20775***	0.0817
Current (Fixed)	1.0000	0.0000
Model statistics		
N (choice sets)	5778	
Log L	-5288.009	
Pseudo-R^2 (%)	28.6	
χ^2 (degrees of freedom)	4244.9*** (15)	

Notes: *, ** and *** denote significance at the 10%, 5% and 1% levels respectively.

The negatively significant interaction between ASC and AGE suggests that compared to young people, older people were not interested in improving the ES. A similar result applies for people who live in rural areas which were captured by variable ASCRURAL. In other words, younger generation who live in urban areas were keen in seeing improved ES. The significant positive signs of the variables ASCINCO and ASCEDU, means that the probability of a respondent who has higher income and well educated agreeing to choose for the improved ES plans increases significantly relative to lower income and less educated respondents.

In order to find whether the IV parameter lies outside the upper bound of the 0 – 1 range, a second test (Wald-statistic) is required (Hensher *et. al*., 2005). In addition, the test also reveals that if the IV parameter in the model is statistically equal to one, then there is no significant different between NL and MNL models. In other words, the NL model should collapse to the MNL model form. The above result shows that the Improved parameter of the IV is significantly different from 1 (Wald-test of 12.098 > 1.96 at the 95% confidence level). Thus, the NL differs significantly from the MNL model. The results also show the explanatory power of the model is satisfactory at 28.6 per cent. The highly significant Chi-square test indicates that the NL model estimated is an improvement in the L Log function of a model estimated with constants only.

Although the NL model partially relaxes the IIA property, it assumes homogeneous preferences across respondents which may also affect the accuracy and reliability of welfare estimation. Iincorporating heterogeneity in the model may provide improved behavioural individual preferences. The ML model was estimated in order to account for preference heterogeneity. Besides it also fully relaxes the IIA assumption.

In the ML model, a distribution for the random parameters is specified and parameters are estimated for that distribution. In this study, the cost coefficient is fixed while other coefficients are allowed to vary. Initially, all the attributes except COST were included as random variables with normal distribution. The ASC, COST, and INCOST were identified as non-random variables with fixed parameter estimates. Estimates were obtained using 1000 random draws to simulate the sample likelihood. Attributes which repeatedly indicate an insignificant standard deviation over the range of draws were then re-estimated with a number of different mixing distributions such as triangular, lognormal and uniform. The results of the ML models are shown in Table 3.

In Model 1, the signs of the random parameters are consistent with *a priori* expectations, and all attributes except WU30 are statistically significant at 99% level. The signs of the non-random parameters are also consistent with *a priori* expectations and statistically significant. The positive and significant sign on the ASC coefficient implies that a positive utility impact occurs in any move away from the status quo. However, improved ES with higher cost contributes negatively to utility and is therefore less likely to be selected. The INCOST variable reveals that higher income respondents are not concerned about cost (payment vehicle) increases. The standard deviations of parameter distributions are assumed to follow normal distribution for all the random parameters except WU30 which is a triangular distribution. The results show that ME10, ME30, NL30, and SV have statistically significant parameter estimates that suggest the existence of heterogeneity in the sampled respondents. In other words, different individuals possess individual specific parameter estimates (η_{ki}) that may be different from the sample population mean parameter estimate (β_k). On the other hand, the insignificant parameter estimates for derived standard deviation of NL10 and WU10 indicate that the dispersion around the mean is statistically equal to zero ($\eta_{ki} = 0$), suggesting that all information in the distribution is captured with the mean (β_k). There is no heterogeneity (considered to have same preferences) amongst respondents in choosing those attributes levels.

Table 3 Mixed Logit (ML) model results

Variable	Model 1		Model 2	
Random Parameters				
ME10	0.21066***	(0.0592)	0.15507**	(0.0663)
ME30	0.45630***	(0.0738)	0.64842***	(0.0964)
NL10	0.33162***	(0.0606)	0.31513***	(0.0696)
NL30	0.88210***	(0.1086)	1.01823***	(0.1295)
WU10	0.26799***	(0.0598)	0.19511***	(0.0653)
WU30	0.01705	(0.0519)	0.14117**	(0.0601)
SV	0.41012***	(0.0615)	0.47132***	(0.0698)
Non-random Parameters				
ASC	0.21279*	(0.1253)	0.29339**	(0.1324)
COST	-0.02766***	(0.0036)	-0.02812***	(0.0038)
INCOST	0.00189***	(0.0004)	0.00189***	(0.0004)
Standard Deviation of Parameter Distributions				
NsME10	0.71620***	(0.1877)	0.78737***	(0.1943)
NsME30	0.89344***	(0.2043)	0.91395***	(0.2034)
NsNL10	0.05275	(0.9733)	0.47340*	(0.2554)
NsNL30	1.25621***	(0.2244)	1.22299***	(0.2205)
NsWU10	0.41132	(0.2806)		
TsWU10			0.97364*	(0.5917)
TsWU30	2.24263***	(0.4728)	2.15555***	(0.4771)
NsSV	0.74452***	(0.1647)	0.76603***	(0.1679)
Heterogeneity in Mean				
ME10: RURAL			0.23138*	(0.1234)
ME30: RURAL			-0.71157***	(0.1398)
NL10: RURAL			0.08382	(0.1084)
NL30: RURAL			-0.45315***	(0.1241)
WU10: RURAL			0.25058**	(0.1157)
WU30: RURAL			-0.46711***	(0.1218)
SV: RURAL			-0.19305**	(0.0807)
Model statistics				
N (choice sets)	5778		5778	
Log L	-5400.850		-5335.634	
Pseudo-R^2 (%)	14.9		15.9	
χ^2 (degrees of freedom)	1896*** (17)		2026*** (24)	

Notes: SE in parentheses; *, ** and *** significance at 10%, 5% and 1% levels.

Albeit unobserved heterogeneity is apparent in Model 1, the model fails to explain the sources of heterogeneity, offering an explanation as to why that heterogeneity may exist. One way of detecting the possible sources of heterogeneity around the means of the random parameters is by interacting the random parameters with other socio-demographic variables in the utility function. After numerous tests of the various interactions of the four attributes with the respondents' socio-economic characteristics collected in the survey, the model that includes RURAL interaction (Model 2) was found to fit the data the best compared to Model 1 in terms of significant coefficients, Log L, pseudo-R^2 and Chi-square. All the random parameters interacted with the rural variables are statistically significant except NL10. The heterogeneity in the mean for higher levels of environmental improvements such as ME30, NL30, and WU30 which are also highly statistically significant with negative signs suggests that differences in the marginal utilities held for those attributes may be, in part, explained by differences between respondents who live in urban and rural areas. In other words, rural respondents are more sensitive (negatively) relative to urban respondents in improving the ES attributes. Similarly, rural respondents are also not in favour of more variety of landscape view compared to urban respondents. While for ME10 and WU10, rural respondents were more willing to support a 10% reduction in methane and water usage attributes in relative to urban respondents.

Model 2 results also show that all random and non-random parameters have *a priori* expectation signs and are statistically significant. Interestingly, the WU30 which was insignificant in Model 1 appeared to be statistically significant at 95% confidence level. This implies that respondents' have positive utility from a 30 percent reduction in water usage for irrigation. The standard deviations of parameters distributions for all the random parameters are statistically significant indicating heterogeneity does exist amongst sampled respondents in choosing those attributes levels. In this model, WU10 is assumed to have a triangular distribution instead of a normal distribution in Model 1.

Overall, these results indicate that positive and significant economic values exist for higher levels of ES attributes of the improved options.

6.0 Estimation of WTP

Once the parameter estimates are obtained via NL and ML models, welfare measures, in the form of marginal WTP or implicit prices, can be determined by estimating the marginal rate of substitution between the change in ES attribute in question and the marginal utility of income represented by the coefficient of the COST (payment vehicle). Despite the fact that the NL has biased estimates due to homogeneous preference assumption, the study reports the results of NL WTP estimates in order to compare the robustness of the models. For the NL, the WTP estimates and its confidence intervals (CI) were calculated based on 1000 random draws using the Krinsky and Robb (1986) procedure. As for the ML random parameters, the WTPs and the CIs were generated using the unconditional parameter estimates (population moments), which are obtained by simulating the population (Hensher *et al*., 2005). Estimates of marginal WTP derived from these models are presented in Table 4. The estimated values are marginal WTP annually for a period of 5 years for a change (improvement) in the ES attributes concerned, *ceteris paribus*.

Table 4 Mean annual marginal WTP (NZ$) per household for the attributes

Attribute	NL	ML
10% reduction in Methane gas emissions	14.06 (5.66 – 22.47)	6.66 (-48.55 – 61.87)
30% reduction in Methane gas emissions	31.31 (20.91 – 41.71)	22.14 (-41.29 – 85.57)
10% reduction in Nitrate leaching to waterways	8.89 (11.66 – 26.13)	11.83 (-22.11 – 45.78)
30% reduction in Nitrate leaching to waterways	57.25 (39.23 – 75.27)	38.55 (-46.32 – 123.42)
10% reduction in water use for irrigation	18.55 (9.61 – 27.50)	8.33 (-14.37 – 31.04)
30% reduction in water use for irrigation	5.71 (-0.26 – 11.68)	8.90 (-41.47 – 59.28)
30% more in scenic views	27.89 (18.16 – 37.61)	17.61 (-36.47 – 71.69)

Confidence intervals (CIs) in parentheses at 95% level; mean WTPs and CIs are calculated using Krinsky and Robb (1986) procedure for NL, and for ML unconditional parameter distribution estimates are used.

The results show that there is some variation across the WTP estimates resulting from the different welfare estimation specifications. The marginal WTP for the ML model has larger confidence intervals compared to NL model, reflecting greater variations in respondents' preferences for these attributes. Since the ML model has better results statistically, its marginal WTP estimates are used in the following discussion. The marginal WTP for all the attributes are positive, implying that respondents have positive utilities for increases in the quality or quantity of each attribute. For example, an improvement in Methane gas emission attribute from current condition (deterioration) to 10% reduction (improvement), an average respondent would be willing to pay $6.66 annually for a period of 5 years. These marginal WTP offer some insights on the relative importance of each attribute, and can be used by policy makers to assign more resources to improving those attributes that have higher values, such as 30% levels of Nitrate Leaching, Methane and Scenic Views. It is also interesting to note that the reduction levels (10% and 30%) in water usage for irrigation are not highly valued by the respondents, an average of $8.62 annually. This is mainly due to the fact that water is a scarce resource for agricultural activities and reducing it may decrease the profitability of pastoral farming and consequently, impact the economic growth of New Zealand.

Table 5 Testing for differences in marginal WTP between NL and ML models

Attribute	ME10	ME30	NL10	NL30	WU10	WU30	SV
$WTP_{NL} - WTP_{ML} > 0$	0.62552	0.61962	0.68398	0.68297	0.77997	0.54677	0.65452

A convolution test developed by Poe *et al*. (2001, 2005) was conducted to assess whether there are any significant differences between the marginal WTP derived from the NL and ML models. The results are shown in Table 5. Based on this test, the annual average marginal WTP for all the ES attributes are not significantly different at 99% level across the models.

7.0 Policy Implications

In order to estimate the respondents' CS or mean WTP for environmental improvements in pastoral farming management over the current deteriorating conditions, four possible options were created for policy analysis. Different combinations of attributes are considered as the outcomes of different management options. The estimates of mean WTP from the NL and ML models for the four scenarios are reported in Table 6. The two models are really treating the data in slightly different ways (in the way a random error term is treated) and therefore it is expected that there are some differences in estimation. Both views might be quite valid. This study recommends using ML model estimation in the following policy discussion due to its better ability to handle heterogeneity in preferences and absence of IIA assumption.

Table 6 Mean annual CS estimates per household associated with different policy options

Attribute	Current	Policy 1	Policy 2	Policy 3	Policy 4
ME reduction	0	10%	30%	10%	30%
NL reduction	0	10%	30%	10%	30%
WU reduction	0	10%	30%	10%	0
SV more	0	30%	30%	0	0
NL - CS ($)		13.88 (-7.63 – 35.39)	18.67 (-3.74 – 41.09)	12.15 (-9.14 – 33.44)	16.59 (-5.29 – 38.48)
ML - CS ($)		24.67 (7.89 – 41.46)	42.57 (4.59 – 80.53)	19.83 (13.06 – 26.61)	34.94 (3.24 – 66.63)

Note: The mean CS and CIs (95% level) are calculated using the Krinsky and Robb (1986) procedure for NL whereas for ML the unconditional parameter distribution estimates are used.

As expected, the CS increases from the current deteriorating conditions towards the better environmental conditions in the pastoral farming. For example, a change from current conditions to improved conditions as in Policy 1, on average, respondents in New Zealand are willing to pay NZ$24.67 each year over 5 years for the specified ES improvements. Similarly, greater improvements in terms of 30% levels under Policy 2 increases the mean WTP to NZ$42.57. In addition, the results also indicate the importance of attributes trade off when calculating WTP for an environmental improvement. For instance, Policy 1 and Policy 3 differ only in terms of landscape effects (with and without SV improvement). The landscape effect reduces the WTP by about 20% in Policy 3 scenario. As for Policy 2 to Policy 4, trading off WU and SC attributes reduces WTP by about 18%. Overall the positive CS implies that respondents on average not only experience greater marginal utilities for improving these selected ES attributes but also are willing to pay more for higher levels of environmental enhancement.

8.0 Conclusion

Intensification of pastoral farming in New Zealand has caused serious environmental effects such as increased nitrate leaching to streams and rivers, increased methane gas emissions, increased demands for surface and groundwater for irrigation and reduced variety in pastoral landscapes. These effects of increased intense pastoral farming reduce the ability of pastoral land to provide some important ES such as clean water and air. In this paper, choice modelling is used to assess New Zealand residents' preferences toward some environmental values Thus, the study surveys randomly selected New Zealand residents to determine their willingness to pay for some environmental attributes: improved water quality, reduced methane gas emissions, reduced demands by agriculture for surface and groundwater, and more diverse pastoral landscapes associated with pastoral farming in the area.

The study applies different model specifications based on their treatment of the IIA and homogeneous/heterogeneity preference assumptions. The MNL model carries the IIA and homogeneous preference assumptions and its parameter estimates are unreliable. The NL model partially relaxes the IIA assumption but maintains the homogeneous preference assumption. The ML model which is the most advanced and flexible model to date in CM method fully relaxes the IIA and homogenous preference. The study concludes that there is a significant increase in New Zealand residents' marginal utilities (i.e., satisfaction) from improvement in all each of the ES attributes. The findings also indicated that respondents are willing to pay more for improving those attributes with 30 per cent reduction levels such as nitrate leaching, methane gas and scenic views. However, water usage for irrigation purpose was not highly valued by the respondents due to the fact that water is a scarce resource for agricultural activities and reducing it may impact the viability of pastoral farming. Finally, the models were then simulated with different policy options to see whether respondents are willing to pay for improved environmental outcomes. The overall welfare estimation results show that respondents not only experience greater marginal utilities for improving these selected ES attributes but also are willing to pay more for higher levels of environmental enhancement.

It has been shown that CM has the flexibility to evaluate both the marginal values of environmental attributes and the welfare impacts of an array of alternative management options. This is important, since resource managers are often concerned with marginal changes in attribute levels between management alternatives. By weighing up these values along with the market values of benefits and costs for the alternative plans, the relevant authorities can identify a management plan that yields the greatest net benefit to society.

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