Nonmarket Valuation of Water Quality: Addressing Spatially Heterogeneous Preferences Using GIS and a Random Parameter Logit Model

Peter Tait*, Ramesh Baskaran, Ross Cullen, Kathryn Bicknell

Department of Accounting, Economics and Finance, PO Box 84, Lincoln University, 7647

New Zealand.

Abstract

The spatial distribution of agro-environmental policy benefits has important implications for the efficient allocation of management effort. The practical convenience of relying on sample mean values of individual benefits for aggregation can come at the cost of biased aggregate estimates. The main objective of this paper is to test spatial hypotheses regarding respondents' local water quality and quantity, and their willingness-to-pay for improvements in water quality attributes. This paper combines choice experiment and spatially related water quality data via a Geographical Information System (GIS) to develop a method that evaluates the influence of respondents' local water quality on willingness-to-pay for river and stream conservation programs in Canterbury, New Zealand. Results showed that those respondents who live in the vicinity of low quality waterways are willing to pay more for improvements relative to those who live near to high quality waterways. The study also found that disregarding the influence of respondents' local water quality data has a significant impact on the magnitude of welfare estimates and causes substantial underestimation of aggregated benefits.

Key words: Water Quality, Choice Experiment, Geographical Information System, Aggregate Benefits

JEL codes: Q51, Q25, Q58

* Corresponding author: peter.tait@lincoln.ac.nz. Ph: 64 3 321 8274

1.0 Introduction

The choices made by researchers when aggregating individual benefits can significantly affect the estimates that are available to be used in cost benefit analysis (Morrison, 2000). Aggregation of environmental values commonly relies on sample mean values of individual benefits. However, individuals' locations in relation to impact sites (proximity) may influence valuation and hence, it is important to account for spatial differences in estimating aggregate benefits (Bateman et al., 2006). Analysis of how values differ spatially within the population being aggregated can mitigate bias by identifying values conditional on spatially related variables that are hypothesised to influence individual preferences.

This paper employed choice experiment (CE) methodology and spatially related water quality data in a Geographical Information System (GIS) to evaluate the influence of local water quality on respondents' willingness-to-pay (WTP) for river and stream conservation programs in Canterbury, New Zealand. Identification and estimation of spatial patterns of nonmarket values have taken many forms in the literature. Hedonic studies are perhaps the most widespread approach to estimating spatial relationships of nonmarket values (MacDonald et al. 2010; Agee and Crocker, 2010; Kong et al., 2007). Travel cost valuation methodology explicitly incorporates geographical locations of respondents into the analysis (Taylor et al., 2010). A growing number of applications of these methods employ GIS tools to enhance accuracy of metrics and spatial modelling (Bateman et al., 2002). Comparison of separate models for individual regions is a traditional approach to investigating spatially differing values (Birol et al., 2006). However, this type of analysis does not systematically incorporate local spatially related variables into models and thus, fails to provide regionally specific benefit estimation.

Application of unadjusted existing nonmarket values to geographic maps has also been used to assess total values of conservation programs (Naidoo and Ricketts, 2006; Egoh et al., 2008; Nengwang et al., 2009, Jenkins et al., 2010). This approach is a rudimentary form of benefit transfer and more sophisticated forms use valuation functions that vary across spatial as well as socio-demographic variables (Bateman et al., 2006; Plummer, 2009). Geostatistical interpolation methods have also been employed to assess the spatial distribution of nonmarket benefits (Campbell et al., 2009). Distance from a site being valued has received significant attention in the literature as a source of spatial preference heterogeneity. Highly significant distance decay in values has been found demonstrating that reliance on sample mean WTP can result in biased estimates (Hanley et al., 2003; Bateman et al., 2006). Concu (2007) was one of the first authors to have conducted a distance decay analysis using CE method. The author concluded that distance omission produces underestimation of aggregate benefits and losses.

Other sources of spatial preference heterogeneity have been identified in a somewhat limited pool of studies outside of the revealed preference and distance decay literature. Brouwer et al. (2010) used CE method to examine spatial preference variability in the valuation of water quality improvements for the Guadalquivir River Basin in the south of Spain. The authors investigate whether respondents' value improvements in their own sub-basin more than three other sub-basins by specifying dummy variables for each of the four sub-basins. Parameters on interactions of these dummy variables with the environmental attributes were estimated. Results indicated that respondents' valued the change of water quality significantly more for their respective sub-basins, but only for the highest level of water quality considered. The authors found that not accounting for spatial preference heterogeneity results in an underestimation of around 30 percent of the estimated value for the highest water quality level in the whole river basin. In an alternative approach, Condon et al. (2007) examined the influence of respondents' geographical location on values for rural land conservation programs in Florida. The study used a 20 kilometre (km) radius around respondents and four variables hypothesised to affect individual values which are constructed using a GIS. Results revealed that the share of agricultural land and distance to the coast are statistically significant influences on respondents' values. The authors found that compared to using sample mean values, aggregate values incorporating the respondents' geographic information were approximately 17 percent and 50 percent lower for the highest and lowest valued programs respectively. Comparing this outcome with that of Brouwer et al. (2010), emphasises that the direction of aggregation bias from using sample mean values is not always obvious *a priori*.

This study considered respondents' local water quality conditions as a source of spatial preference heterogeneity in valuing stream and river conservation programs in Canterbury. While providing specific policy advice to regional water managers, this study also has wider implications. Firstly, this paper contributes to the overall spatial preference heterogeneity literature, where evidence in New Zealand is limited. Secondly, this study provides an application supporting the use of methods that integrate spatial analysis into valuation exercises that enhances welfare estimates.

2. Background

Canterbury is the largest region in New Zealand, with an area of 45,346 km^2 and a population of approximately 500,000 (SNZ, 2007). Environment Canterbury is the regional council for Canterbury and is responsible for a wide variety of functions including environmental monitoring and investigations, regional policy and planning, water permits and discharge permits. The Canterbury region has a 160 year history of agricultural production and is currently experiencing a significant trend in water intensive dairy farming replacing traditional dry land pastoral and arable farming. Dairy stock unit numbers have increased rapidly and continue to do so. The environmental implications of these land use changes and intensification of production have been extensively researched with a growing body of scientific literature outlining the impending consequences if inadequate action is taken. Studies of trends in water quality and contrasting land cover indicate a positive relationship between dairy stock numbers and decreasing water quality (Larned et al., 2004). Increases in water borne pathogens such as Campylobacter have been reported (Ross and Donnison, 2003) and there are risks of irreversible damages of land application of animal effluent as long term consequences are not well understood (Wang and Magesan, 2004). The rate of fertiliser and pesticide applications has increased dramatically over the past decade and are forecast to continue increasing (PCE, 2004) with evidence of increases in nitrogen and dissolved reactive phosphorous in waterways (Cameron and Di, 2004). There has been a significant increase in groundwater abstraction associated with land use intensification, contributing to a decline in groundwater levels and reduced flows in rivers and lowland streams. Environment Canterbury records show a 260 per cent increase in the amount of irrigated land from 1985 to 2005, and some 70 per cent of consumptive use of water in the region is for pastoral purposes. Increased irrigation allows more intensive use of land and leads to increased agricultural production.

In the application of agri-environmental water quality policy, some progress has been made in reducing point sources of pollution, however, non-point sources remain difficult to manage. Recent water quality planning has spurred development of policies such as the Dairying and Clean Streams Accord that targets farming practices on dairy farms, the Restorative Programme for Lowland Streams that aims to return water to dry streams and ensure minimum environmental flows, and the Living Streams project that encourages sustainable land use and riparian management practices.

3. Method

This study employed a CE to estimate the benefits of environmental policies aimed at reducing agricultural impacts on Canterbury waterways.[1] The respondent is presented with choice sets made up of several alternatives and each alternative is made up of combinations of environmental attributes reflecting policy outcomes. Combinations of attributes and their levels are varied systematically in the alternatives according to experimental design theory. The respondent is asked to choose the alternative from a choice set with the combination of attribute levels (policy outcomes) they prefer most. The resulting data are analysed using probabilistic models that relate the probability of an alternative being chosen to the levels of the attributes.

The development of the set of attributes to be valued consisted of two main procedures. First, a survey was conducted of relevant policy documents and expert based opinion of Environment Canterbury policy analysts. Second, focus groups and cognitive interviews (Dillman, 2007) were carried out with rural and urban Canterbury residents. Three environmental attributes were identified to be included in the CE and these are shown in Table 1. The cost attribute is defined as an annual household payment via council rates. The payment vehicle was framed as an ongoing annual cost as participants of resident focus groups and interviews indicated that they considered that funding would be required continuously for policy activities such as monitoring and enforcement.

Insert Table 1 here

[1] Louviere et al. (2000) provides a thorough presentation of choice experiments for the interested reader.

The first water quality attribute is the risk of people getting sick from pathogens in animal wastes that end up in waterways. Exposure is by way of recreational contact, and risk is measured as the number of people out of one thousand that would become sick annually. This type of presentation of risk has been used elsewhere to value risk tradeoffs in water quality attributes (Adamowicz, 2007). The magnitude of changes in levels was guided by studies that examined current and potential water borne pathogen risks to human health in New Zealand (McBride et al., 2002).

The second water quality attribute allowed us to value the impact of excess nutrients on the ecological quality of rivers and streams. The descriptions of the ecological levels for water quality were in accord with Environment Canterbury measurement using the Quantitative Macro Invertebrate Index developed by them. Table 2 shows the descriptions used.

Insert Table 2 here

The third water quality attribute was used to value the impact of low-flow conditions. This attribute was measured as the number of months that a river is in low-flow. A waterway is experiencing low-flow conditions when the flow rate falls below a minimum level necessary to protect recreational and ecological quality. The description of the impact of low-flow conditions on rivers and streams followed New Zealand Ministry for the Environment recommendations and the range in levels was guided by flow rate data from the Environment Canterbury website (www.ecan.govt.nz).

The experimental design involved three attributes with three levels and the cost attribute with six levels (3^3 x 6^1) which were combined in a D-efficient fractional factorial main effects experimental design, providing 18 profiles. The choice sets were constructed following the procedure proposed by Street et al. (2005) which were then randomly blocked into 3 versions of 6 choice sets. Each choice question had three alternatives and the third alternative was always a constant base alternative (current condition). This meant that each respondent in each choice set had to choose either an improved environmental management plan (Alternative 2 or 3) or the current plan (Alternative 1). The constant base alternative was assumed to be a worsening condition of rivers and streams if no change in management occurs. In this alternative, there is no additional payment by the household, however it is assumed that the risk of getting sick will be at its greatest level, ecological quality will be at its lowest level, and the number of low-flow months will be at its highest level.

The survey consisted of three sections. The first section sought to measure respondents' attitudes towards agri-environmental policy in Canterbury, and to indicate how rivers and streams are important to them. The second section consisted of the choice sets and the third section concluded with household socio-demographic questions. The first and third sections were designed to capture preference heterogeneity that was not captured by the attributes in the choice sets.

The variation generated between the attribute levels and the alternative chosen is modelled using a discrete choice probabilistic method where the dependent variable is the probability of choosing an alternative given the levels of attributes in that chosen alternative. This study fits a Random Parameter Logit (RPL) model to the data obtained in the CE.[2] The deterministic part of the individual indirect utility function estimated takes the general functional form:

$$V_{ij} = ASC_j + \sum_k \beta_k X_{ijk} + \sum_k \eta_{ki} X_{ijk} + \sum_m \omega_{jm} ASC_j * S_{mi} + \sum_n \delta_{kn} X_{ijk} * S_{ni} \quad (1)$$

where *ASC* is an alternative specific constant for alternative *j*, β_k is a vector of coefficients associated with the *k*th attribute, *X* includes household cost as well as the attributes that describe water quality, η_{ki} is a vector of *k* deviation parameters which represents how the tastes of individual *i* differ from the average taste (β_k), ω_{jm} is the vector of coefficients of the interactions between the *ASC* and the *m*th socioeconomic characteristic of individual *i* (S_{mi}) and δ_{kn} is the vector of coefficients of the interactions between the *k*th attribute and the *n*th local water quality characteristic of individual *i* (S_{ni}). This last element of the utility function contained the respondents' local water quality data that is hypothesised to influence their WTP for the attributes contained in *X*.

The choice data were analysed using NLOGIT 4.0™ statistical software. Model variables are summarised in Table 3. The attributes are effects coded into two variables for each attribute with the lowest level of quality being the fixed comparator for each attribute; Ecology Fair (coded 1 if Fair, 0 if Good, -1 if Poor) and

[2] Readers who are seeking an in-depth discussion of this model can refer to Train (2003).

Ecology Good (coded 1 if Good, 0 if Fair, -1 if Poor); Risk10 (1 if Risk10, 0 if Risk30, -1 if Risk60) and Risk30 (1 if Risk30, 0 if Risk10, -1 if Risk60); Flow1 (1 if Flow1, 0 if Flow3, -1 if Flow5) and Flow3 (1 if Flow3, 0 if Flow1, -1 if Flow5). The non-attribute variables were interacted with the alternative specific constant.

Insert Table 3 here

The most common distributional functional forms for parameters are normal, lognormal, uniform and triangular. After evaluating the results from various distributional functional forms, we followed Hensher and Greene (2003) and opted for a bounded triangular distribution for all attributes. In order to take into account the degree of heterogeneity whilst obtaining meaningful WTP estimates, the spread of each random parameter distribution was restricted to be equal to the mean.[3] Five hundred shuffled Halton draws were used in maximising the simulated Log-likelihood function. To examine if the effects coded variables for an attribute should be combined into a single linear variable, a Wald test was conducted to observe whether the two parameters (one for each of the two effects coded attribute levels) are equal. The null hypothesis of equality was rejected for all attributes. Thus, preferences for the two attribute levels are statistically significantly different.

3.1 Water Quality Data and GIS

Three spatially related water quality datasets hypothesised to influence respondents' values of attributes were imported into the Geographical Information System ArcView 9™, along with respondents' geocoded addresses. Water quality data points geographically closest to respondents, one for each of the three water quality variables, were obtained for use in econometric models. Table 4 shows the current distribution of respondents' local water quality measures.

Insert Table 4 here

The first dataset contained weekly Suitability for Recreation Grades (SRG) for 56 sites over the period of 2007 to 2008 February. The grades are based on a qualitative risk assessment of the susceptibility of a water

[3] See Hensher and Greene (2003) and Hensher et al. (2005) for a description of the triangular distribution in this context.

body to faecal contamination, and a measurement of the faecal indicator, E. coli. There are five grades and the risk of becoming sick increases from very good to very poor grades with sites graded poor and very poor unsuitable for recreational contact. The inclusion of this data facilitated the testing of the spatial hypothesis that respondent's local SRG influences their WTP to decrease the risk of becoming sick.

The second dataset consisted of Semi Quantitative Macroinvertebrate Community Index (SQMCI) scores for 431 sites. This index uses measures of the abundance and diversity of aquatic invertebrates as an indicator of ecosystem health. The presence of pollution sensitive macroinvertebrates indicates that the body of water is healthy while the excessive presence of pollution tolerant macroinvertebrates indicates poor water quality. The inclusion of this data aided the testing of the spatial hypothesis that respondents' local SQMCI score influences their WTP for improvements in ecological quality.

The third dataset contained daily flow rate measures for 70 sites. In order to indicate which rivers were experiencing low flows relative to historical trends, the flow sites were categorised into stratum describing how flow levels have changed according to daily median flow for the last hydrological year relative to the median daily flow rate over the entire data series. The increase stratum ranged from 5% to 15% increased flow. The inclusion of this data assisted the testing of the spatial hypothesis that respondents' local flow changes influence their WTP to decrease the number of low-flow months. These three spatial hypotheses were tested by interacting each of the respondents' water quality measures with the cost attribute. The parameters of these variables were then incorporated into the estimation of respondents' WTP for improvements in the attribute relevant to the water quality measure using the following equation:

$$\text{Marginal WTP Attribute X} = -\left(\frac{\beta_{\text{k}}}{\beta_{\text{Cost}} + \beta_{\text{Water Quality Measure}_{rl}\text{*Cost}} \times \text{Water Quality Measure}_{\text{rl}}}\right) \quad (2)$$

where Water Quality Measure$_{rl}$ = SRG (Very Poor to Very Good), SQMCI (0 to 2,..>7) or Flow Change (Increase to >50% decrease)

The above equation was applied by Baskaran et al. (2009) in a similar approach valuing environmental attributes by stratifying respondents based on income levels. In this study, equation (2) stresses the importance of including the interactions between the key water quality variables (SRG, SQMCI and Flow Change) and the selected attributes to provide extra information to policy makers on the effect in the estimated welfare measures for a particular level of water quality.

The value of benefits from combinations of attribute level changes conditional on respondents' local water quality can be calculated as Compensating Surplus (CS) estimates. Estimates of CS were calculated using a modified standard Hanemann (1984) utility difference expression:

$$\mathrm{CS}_i = -\left(\frac{1}{\beta_{\mathrm{Cost}} + \sum_r \left(\beta_{\mathrm{Water\ Quality\ Measure}_{rl}\mathrm{*Cost}} \times \mathrm{Water\ Quality\ Measure}_{\mathrm{rl}} \right)} \right) \left(V_{ij}^{0} - V_{ij}^{1} \right) \qquad (3)$$

where V_{ij}^{0} is the utility derived from 'No change' base alternative, and V_{ij}^{1} is the utility derived from new management alternatives. The following are the 'No Change' (V_{ij}^{0}) and the two new management scenarios (V_{ij}^{1}) employed in this study:

No change	60 people per 1000 get sick from recreational contact each year, ecological quality is poor, and there are 5 months of low-flow conditions.
Management Fair	30 people per 1000 get sick from recreational contact each year, ecological quality is fair, and there are 3 months of low-flow conditions.
Management Good	10 people per 1000 get sick from recreational contact each year, ecological quality is good, and there is 1 month of low-flow conditions.

3.2 Survey Logistics

During the months of July and August 2008, 1500 surveys were mailed to Canterbury residents using random sampling stratified by Territorial Local Authority to achieve a geographically representative sample.

Reminder postcards were sent out after two weeks, followed by another survey instrument sent to those yet to respond a further week on. No incentives were given to complete the survey. The mail-out procedure yielded 349 usable responses with an effective response rate of 25 percent. In order to assess if the sample was representative of the Canterbury population, Chi-square tests were conducted. If the null hypothesis is rejected, it can be concluded that the Census 2006 population data were statistically significantly different from the sample data. It is apparent that the null hypotheses was rejected for income, education and house tenure. This means that the sample respondents have higher income, are more educated and have a higher home ownership rate.This may indicate sample selection bias toward affluent and educated groups and thus, caution should be taken when using these variables in the WTP estimation. However, the combination of employing an RPL model and water quality data should account for this bias in terms of individual heterogeneity within income groups and spatial differences amongst respondents when valuing attributes. To consider the geographical representation of the sample, a Chi-square test was conducted for the distribution of respondents according to the regions ten Territorial Local Authorities (TLA). Results showed that the Census and sample distributions are not statistically significantly different.

A relevant concern when conducting a CE in which the experimental design is blocked is whether a sample contains a sufficient representation of the choice sets. The distribution of the three blocks of the experimental design used in this survey was 32%, 33% and 34%, and therefore, the returned surveys represented the choice sets adequately.

4. Results and Discussion

All parameters except Flow 1 are highly statistically significant and of the expected signs. The standard deviation parameters for all attributes except Flow 1 are statistically significant suggesting significant taste heterogeneity exists within the data for these attributes. These factors alongside the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and McFadden Pseudo R^2 form the basis for a test of relative model fit. The Psuedo-R^2 in Table 5 shows that the fully specified model has an acceptable level of explanatory power. Improvements in the levels of the attributes increase the probability of that option being chosen, with the magnitude of the probability increasing as the attribute level improves. All attributes except Flow3 are statistically significant at the 1% level. This indicates that respondents did not prefer the medium level of improvement of three months of low-flow but would rather see the highest level of improvement of one month of low-flow conditions. Respondents with higher household income and being a female increased the probability of choosing an alternative with improvements in water quality. Respondents who agreed that agricultural practice is environmentally safe were less likely to choose an alternative with improvements in water quality. Respondents who concurred that farmers should pay for water quality improvement programs were less likely to choose an alternative with improvements in water quality. Similarly, respondents who indicated that commercial use of water is important were less likely to choose an alternative with improvements in water quality. In view of interactions between the water quality and cost attributes, it is apparent that the estimated coefficients for SRG, Flow Change and SQMCI are significant at the 1%, 5% and 10% levels, respectively.

Insert Table 5 here

4.1 WTP and CS Estimates

Table 6 shows WTP for three bands of water quality data for each attribute. The water quality data are averaged within the three bands. In generating Table 6 we first apply equation two without incorporating any information about respondents' local water quality. Equation two thus simplifies to the ratio of attribute and cost coefficients, yielding the last column of Table 6. The incorporation of respondents' local water quality adds the product of a water quality interaction coefficient and quality level to the denominator of equation 2. This is calculated for each attribute and associated water quality level resulting in the middle three columns of Table 6.

Insert Table 6 here

Looking at Table 6 we see that respondents' WTP increases as water quality deteriorates. Respondents with low SRG have higher WTP in order to reduce the risk of getting sick relative to respondents with high SRG. Respondents with low SQMCI scores have higher WTP in order to improve ecological quality relative to respondents with high SQMCI scores. Respondents who experience a high number of low-flow months are willing to pay more so as to reduce the number of low-flow months relative to respondents who experience a low number of low-flow months. It is also interesting to note that there is a substantial difference in terms of absolute mean WTP values between the respondents' local water quality grades and the overall sample mean estimates. Thus, accounting for respondents' local water conditions in nonmarket valuation can lead to WTP changing considerably. This suggests that valuing water quality attributes by stratifying individuals based on close proximity to rivers and streams may enhance reliability of welfare measures. As mentioned, more affluent and more educated respondents are overrepresented in the sample and as a result, may over or under estimate the 'true' WTP if we rely on the traditional sample mean WTP estimation approach.

Compensating Surplus (CS) measures policy outcomes that indicate WTP for a change in water quality from the 'No Change' option presented in the choice sets to a combination of attributes that depict water quality improvements (Fair and Good Management Scenarios). Calculating Canterbury spatially weighted aggregate CS that takes into account the influence of respondents local water quality involves identifying the percentage of respondents who live in the combinations of the three water quality variables (SRG, SCMI Flow Change) multiplied by both the number of households in Canterbury and average CS estimates as shown in Table 7. For example, in the first row 24 per cent of the sample faced this combination of water quality variables and associated CS values calculated using equation 3. To form an estimate for the Good Management scenario for Canterbury we first assume that 24 per cent of the policy target also face this combination and multiply the $141 individual household estimate by 24 per cent of the 201,660 households in the Canterbury region (SNZ, 2007), yielding $6.7 million. Results of this calculation for each combination of water quality variables are shown in Table 7 as weighted aggregates. Summing these values produces the $27.4 million estimate presented in Table 8.

Insert Table 7 here

Table 8 also presents estimates using sample mean values where CS estimates do not account for respondents' close proximity to river and stream water quality characteristics. This enables a comparison of the CS estimates with and without local water quality data. In order to aggregate the CS across the population, assumptions have to be made about the non-respondents who did not return the survey. For illustrative purpose, we calculate the average aggregate CS based on different multiplier assumptions as suggested by Mitchell and

Carson (1989). We calculated aggregate CS based on the multipliers 0, 0.5 and 1. If 0 is used as a multiplier, we assume that non-respondents are not willing to pay anything. If the multiplier is 0.5, we assume that each non-respondents' WTP is half of the WTP of a sample respondent. The third assumption is that non-respondents have the same mean WTP as respondents and the multiplier is 1. The results of these calculations are presented in Table 8.

Insert Table 8 here

In Table 8, it is noticeable that the aggregation that takes into account the respondents' local water quality data is 125 per cent higher for the Fair Management scenario ((22.9 - 10.2)/10.2) and 130 per cent higher for the Good Management scenario ((27.4 - 11.9)/11.9) assuming non-respondents have the same mean WTP as sample respondents. This suggests that water management programs in Canterbury would be undervalued if the traditional sample mean CS was used to assess aggregate benefits. Using respondents' local water quality data facilitated a more accurate reflection of the distribution of benefits and thus a more appropriate estimation method. The increase in CS from base to Fair and Good Management scenarios indicate that respondents' local rivers and streams are generally poor in quality and are willing to pay more for higher levels of improvements in water quality.

5. Policy Implications and Conclusions

The results reported in this paper have important policy implications for both agri-environmental policy managers and for choice modelling practitioners. For policy managers, practical application of policies with strict budget constraints inevitably necessitates trade-offs being made. The trade-offs could be based upon aspects of water quality, which rivers and streams are to be targeted, and which one to be chosen first. The results of this study may help to answer these questions. First, recognizing the importance of the selected attributes that require greatest attention can be considered. Based upon the results from this study, Canterbury residents will benefit most by improving the ecological quality, followed by reducing the risk of sickness and finally, by reducing the number of months that a river is in low-flow. Secondly, by showing that further benefit is gained by initially targeting the relatively lower quality rivers and streams. For policy practitioners, by modelling the relationship between the GIS based water quality data applying the method developed in this paper, they will be able to use the estimated values as proxies of benefits to evaluate policy actions across rivers and streams within Canterbury.

Implications for choice modelling practitioners stem from the finding that individual welfare is spatially sensitive, and that omission of this facet from aggregate CS calculations may bias results. The primary purpose of this paper was to test spatial hypotheses regarding respondents' local water quality and quantity, and their WTP for improvements in water quality attributes. We found that WTP is sensitive to local water quality. This paper also presented aggregate benefit values that are suitable for cost-benefit analysis. Benefits of combinations of policy outcomes can be assessed using CS estimates. This study found that inclusion of respondents' local water quality data has a significant impact on the magnitude of CS estimates. Aggregate CS estimates that incorporate spatially related water quality data are more than 100 per cent larger than traditional sample mean CS estimates.

The main contribution of this paper is the development of a method to incorporate respondents' local water quality data via GIS in estimating WTP and CS for agri-environmental policy. By including respondents' local water quality data, the analyst is able to form a range of estimates dependent on the specific areas of water quality. In short, the spatially distributed WTP estimates for highest (lowest) levels of improvements in water quality attributes are greater (smaller) than the sample average WTP. Therefore, benefit aggregation based on sample average WTP with no spatially distributed water quality information may result in biased estimates. Further research investigating the spatial impact of policies is needed to form a better understanding of how individual benefits relate to the costs of policy implementation. That analysis could also be conducted employing GIS and, combined with spatial WTP data, could aid in identifying where policy is achieving a net benefit.

Acknowledgements

Funding for this research was provided by the Agricultural and Marketing Research and Development Trust, www.agmardt.org.nz, and Lincoln University. The authors thank Brad Case (Lincoln University) for his valuable assistant in the GIS application. Environment Canterbury staff are also thanked for providing the spatial water quality data. Any errors in this paper are the authors' sole responsibility.

References

Adamowicz, W., Dupont, D., Krupnik, A., Zhang, J., 2007. Valuation of cancer and microbial risk reductions in municipal drinking water: An analysis of risk context using multiple valuation methods. Resources for the Future, Washington, DC. Available at www.rff.org.

Agee, M.D., Crocker, T.D., 2010. Directional heterogeneity of environmental disamenities: the impact of crematory operations on adjacent residential values. Applied Economics 42, 1735-1745.

Baskaran, R., Cullen, R., Colombo, S., 2009. Estimating Values of Environmental Impacts of Dairy Farming in New Zealand. New Zealand Journal of Agricultural Research 52, 377-389.

Bateman, I.J., 2006. The aggregation of environmental benefit values: Welfare measures, distance decay and total WTP. Ecological Economics 60, 450-60.

Bateman, I.J., Jones, A.P., Lovett, A.A., Lake, I.R., Day, B.H., 2002. Applying geographical information systems (GIS) to environmental and resource economics. Environmental and Resource Economics 22, 219-269.

Birol, E., Smale, M., Gyovai, A., 2006. Using a choice experiment to estimate farmers' valuation of agrobiodiversity on Hungarian small farms. Environmental and Resource Economics 34, 439-469.

Brouwer, R., Martin-Ortega, J., Berbel, J., 2010. Spatial preference heterogeneity: A choice experiment. Land Economics 86, 552-568.

Cameron, K.C., Di, H.J., 2004. Nitrogen leaching losses from different forms and rates of farm effluent applied to a Templeton soil in Canterbury, New Zealand. New Zealand Journal of Agricultural Research 47, 429-37.

Campbell, D., Hutchinson, W.G., Scarpa, R., 2009. Using choice experiments to explore the spatial distribution of willingness to pay for rural landscape improvements. Environment and Planning 41, 97-111.

Concu, G.B., 2007. Investigating distance effects on environmental values: a choice modelling approach. The Australian Journal of Agricultural and Resource Economics 51, 175-194.

Condon, B., Hodges, A., Matta, R., 2007. Public preferences and values for rural land preservation in Florida. Selected paper prepared for presentation at the American Agricultural Economics Association Annual Meeting. Portland, OR, July 29-August 1.

Dillman, D.A., 2007. Mail and internet surveys: The tailored design method. Hoboken, N.J: John Wiley & Sons.

Egoh, B., Reyers, B., Rouget, M., Richardson, D.M., Le Maitre, D.C., van Jaarsveld, A.S., 2008. Mapping ecosystem services for planning and management. Agriculture, Ecosystems and Environment 127, 135–140.

Hanemann, M.W., 1984. Discrete/Continuous models of consumer demand. Econometrica 52, 541-562.

Hanley, N., Schlapfer, F., Spurgeon, J., 2003. Aggregating benefits of environmental improvements: distance-decay functions for use and non-use values. Journal of Environmental Management 68, 297–304.

Hensher, D.A., Greene, W.H., 2003. The mixed logit model: the state of practice. Transportation 30, 133 -176.

Hensher, D.A., Rose, J. M., Greene, W. H., 2005. The implications on willingness to pay of respondents ignoring specific attributes. Transportation 32, 203-222.

Jenkins, A.W., Murray, B.C., Kramer, R.A., Faulkner, S.P., 2010. Valuing ecosystem services from wetlands restoration in the Mississippi Alluvial Valley. Ecological Economics 69 1051-1061.

Kong, F., Yin, H., Nakagoshi, N., 2007. Using GIS and landscape metrics in the hedonic price modelling of the amenity value of urban green space: A case study in Jinan City China. Landscape and Urban Planning 79, 240-252.

Larned, S.T., Scarsbrook, M.R., Snelder, T.H., Norton, N.J., Briggs, B.J.F., 2004. Water quality in low-elevation streams and rivers of New Zealand: recent state and trends in contrasting land-cover classes. New Zealand Journal of Marine and Freshwater Research 38, 347-66.

Louviere, J.K., Hensher, D.A., Swait, J., 2000. Stated choice methods: Analysis and application. Cambridge University Press, Cambridge.

MacDonald, D.H., Crossman, N.D., Mahmoudi, P., Taylor, L.O., Summers, D.M., Boxall, P.C., 2010. The value of public and private green spaces under water restrictions. Landscape and Urban Planning 95, 192-200.

McBride, G., Till, D., Ryan, T., Ball, A., Lewis, G., Palmer, S., Weinstein, P., 2002. Freshwater Microbiology Research Programme. Pathogen occurrence and human health risk assessment analysis. Ministry for the Environment & Ministry of Health, Wellington, New Zealand. Available at www.mfe.govt,nz.

Mitchell, R.C., Carson, R.T., 1989. Using surveys to value public goods: The Contingent Valuation Method. Washington, Resources for the Future.

Morrison, M., 2000. Aggregation biases in stated preference studies. Australian Economic Papers 39, 215-230.

Naidoo, R., Ricketts, T. H., 2006. Mapping the economic costs and benefits of conservation. Public Library of Science Biology 4, 2153-2163.

Nengwang, C., Huancheng, L., Wang, L., 2009. A GIS-based approach for mapping direct use value of ecosystem services at a country scale: Management implications. Ecological Economics 68, 2768-2776.

Parliamentary Commissioner for the Environment, 2004. Growing for good: Intensive farming, sustainability and New Zealand's environment. Wellington, New Zealand.

Plummer, M.L., 2009. Assessing benefit transfer for the valuation of ecosystem services. Frontiers in Ecology and the Environment 7, 38-45.

Ross, C., Donnison, A., 2003. Campylobacter and farm dairy effluent irrigation. New Zealand Journal of Agricultural Research 46, 255-62.

Statistics New Zealand, 2007. Census 2006 Table Builder. Available at www.stats.govt.nz. Accessed July 1 2008.

Street, D.J., Burgess, L., Louviere, J.J., 2005. Quick and easy choice sets: Constructing optimal and nearly optimal stated choice experiments. International Journal of Research in Marketing 22, 459-470.

Taylor, G.R., McKean, J.R., Johnson, D., 2010. Measuring the location value of a recreation site. Journal of Agricultural and Resource Economics 35, 87-104.

Train, K.E., 2003. Discrete choice methods with simulation. Cambridge University Press, U.K.

Wang. H., Magesan. G.N., 2004. An overview of the environmental effects of land application of farm effluents. New Zealand Journal of Agricultural Research 47, 289-403.

Table 1: Attributes and levels used in choice sets

Attribute	Base level	Improvement level
Health Risk	60	10 and 30 people/1000/year
Ecology	Poor	Fair and Good
Flow	5	1 and 3 months of low-flow/year
Cost	$0	$15, $30, $45, $60, $75, $90 per domicile per year

Table 2: Ecology attribute level definitions

Poor Quality	Weeds are the only aquatic plants present and cover most of the stream channel. The stream-bed is covered mostly by thick green algae mats. Only pollution tolerant insect populations are present. No fish species are present.
Fair Quality	About 50% of stream channel covered by plants. Few types of aquatic plants, insects and fish. Algae cover about 20% of stream bed. Population densities are reduced.
Good Quality	Less than 50% of stream channel covered by plants. Algae cover less than 20% of stream-bed; there is a diverse and abundant range of aquatic plants, fish and insects. Insect communities are dominated by favourable species with pollution sensitive populations present.

Table 3: Model variables

Risk 10	10 people/1000/year sick from recreational contact

Risk 30	30 people/1000/year sick from recreational contact
Ecology Good	Ecological quality is good
Ecology Fair	Ecological quality is fair
Flow 1	1 month of low-flow/year
Flow 3	3 months of low-flow/year
Cost	\$15, \$30, \$45, \$60, \$75 and \$90 per household per year
ASC	Alternative specific constant 1 if alternative 2 or 3, 0 otherwise
Income	Household gross annual income
Safe	Respondent agrees that agriculture is environmentally safe
Commercial	Respondent indicates commercial use of water is important
Businesses	Respondent indicates farms should pay for water improvement policy
SRG	Measure of pathogen presence
SQMCI Score	Measure of ecological quality
Flow Change	Change in flow conditions

Table 4: Distribution of respondents' local water quality

SRG	% of Sample	SQMCI Median Score	% of Sample	Flow Change	% of sample
Very Poor	70	0 to 2	13	Increase	6
Poor	4	2 to 3	26	0 to 10% decrease	44
Fair	7	3 to 4	17	10% to 20% decrease	9
Good	4	4 to 6	24	20% to 30% decrease	14
Very Good	15	6 to 7	11	30% to 40% decrease	18
		> 7	9	> 50% decrease	9

Table 5: Random Parameter Logit model

Random Parameters	**Coefficient**	**Standard error**
Risk 10	0.496***	(0.06)

Risk 30	0.201***	(0.06)
Ecology Fair	0.249***	(0.66)
Ecology Good	0.701***	(0.08)
Flow 1	0.329***	(0.07)
Flow 3	-0.108	(0.07)
Cost	-0.057***	(0.01)
Non-random Parameters		
ASC	0.317	(0.41)
Safe	-1.28***	(0.25)
Commercial	-1.23***	(0.37)
Gender	0.699***	(0.25)
Income	0.183***	(0.06)
Businesses	-6.13***	(0.46)
SRG x Cost	0.0046***	(0.001)
Flow Change x Cost	0.0056***	(0.001)
SQMCI x Cost	0.0018*	(0.0001)
Derived Standard Deviations of Random Parameter Distributions		
Risk 10	0.496***	(0.06)
Risk 30	0.402***	(0.13)
Ecology Fair	0.249***	(0.06)
Ecology Good	0.701***	(0.08)
Flow 1	0.329***	(0.07)
Flow 3	0.108	(0.07)
Cost	0.057***	(0.01)
Model statistics		
Log Likelihood	-1464	
McFadden Pseudo R^2	0.37	
AIC	1.41	
BIC	1.45	
Observations	2094	

*, **, *** indicates significance at 10, 5 and 1% level.

Table 6: Willingness-to-Pay (2008 NZ$ per annum)

Attributes and Water Quality Variables	WTP ($) Using Local Water Quality			Sample Mean WTP($): Without Local Water Quality
SRG	**< 2**	**2 ≤ grade ≤ 4**	**4 <**	
Risk 10	20.5 (0.6 - 0.3)	16.6 (1.3 - 31.9)	14.1 (1.6 - 6.5)	19.1 (2.2 - 34.6)
Risk 30	16.1 (2.3 - 4.5)	13.1 (1.4 - 27.5)	11 (0.9 - 22.9)	14.9 (2.4 - 20.9)
SQMCI	**≤ 2**	**2 < score < 5**	**5 ≤**	
Ecology Good	27.4 (6.4 - 49)	24.7 (5.8 - 43.4)	23.1 (5.7-0.6)	25.6 (8.5 - 41.3)
Ecology Fair	18.9 (4.5 - 4.1)	17 (3.7 - 30.3)	15.9 (3.6-8.2)	16.1 (4.7 - 26.6)
Flow Change	**> 30% less**	**Up to 30% less**	**Increase**	
Flow 1	15 (4.7 - 27.5)	9.6 (2.7 - 18.8)	5.7 (1.7-12.9)	7.1 (1.6 - 13.4)

95% Confidence intervals in brackets calculated from unconditional parameter distribution.

Table 7: Compensating Surplus (2008 NZ$ per annum)

Local Water Quality			Respondent Distribution	Individual Compensating Surplus ($)		Weighted Aggregate CS ($000's)
SRG	**Flow change**	**SQMCI**		**Fair Management**	**Good Management**	**Good Management**
< 2	up to 30% less	2 < Score < 5	**24%**	118 (33 - 203)	141 (20 - 262)	6,730
< 2	up to 30% less	5 ≤	**16%**	106 (39 - 174)	127 (28 - 225)	4,050

< 2	> 30% less	2 < Score < 5	**11%**	147 (33 - 260)	177 (20 - 330)	4,044
< 2	up to 30% less	≤ 2	**10%**	132 (30 - 236)	158 (14 - 304)	3,043
2 ≤ grade ≤ 4	up to 30% less	2 < Score < 5	**7%**	100 (42 - 160)	119 (32 - 208)	1,765
< 2	> 30% less	5 ≤	**5%**	132 (30 - 236)	158 (13 - 304)	1,565
4 <	up to 30% less	2 < Score < 5	**4%**	83 (44 - 122)	98 (37 - 160)	851
4 <	> 30% less	2 < Score < 5	**3%**	97 (43 - 152)	115 (33 - 197)	744
4 <	up to 30% less	5 ≤	**3%**	77 (44 - 111)	91 (37 - 146)	683
2 ≤ grade ≤ 4	> 30% less	2 < Score < 5	**3%**	124 (31 - 217)	147 (16 - 280)	776
2 ≤ grade ≤ 4	up to 30% less	5 ≤	**2%**	92 (43 - 141)	109 (35 - 185)	531
2 ≤ grade ≤ 4	> 30% less	5 ≤	**2%**	111 (38 - 184)	132 (27 - 238)	560
< 2	Increase	5 ≤	**2%**	77 (44 - 111)	91 (37 - 146)	314
< 2	Increase	2 < Score < 5	**2%**	83 (44 - 122)	98 (37 - 160)	417
< 2	> 30% less	≤ 2	**1%**	168 (16 - 322)	201 (8 - 396)	244
2 ≤ grade ≤ 4	up to 30% less	≤ 2	**1%**	111 (38 - 184)	132 (27 - 238)	232
4 <	> 30% less	5 ≤	**1%**	89 (44 - 135)	106 (36 - 176)	321
4 <	Increase	5 ≤	**1%**	61 (40 - 82)	72 (36 - 109)	87
4 <	Increase	2 < Score < 5	**1%**	64 (42 - 87)	76 (36 - 116)	88
4 <	up to 30% less	≤ 2	**1%**	89 (44 - 135)	106 (36 - 176)	306

95% Confidence intervals in brackets calculated from unconditional parameter estimates.

Table 8: Canterbury Aggregate Compensating Surplus (2008 NZ$ millions/annum)

Aggregation multiplier	α = 1		α = 0.5		α = 0	
Management scenario	Fair	Good	Fair	Good	Fair	Good
Spatially weighted CS aggregation	22.9	27.4	13.7	17.1	5.6	6.7
Sample mean CS aggregation	10.2	11.9	6.3	7.4	2.5	2.1