Incorporating Local Water Quality in Welfare Measures of Agri-environmental Policy: A Choice Modelling Approach Employing GIS

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Paper prepared for presentation at the EAAE 2011 Congress
Change and Uncertainty
Challenges for Agriculture,
Food and Natural Resources

August 30 to September 2, 2011
ETH Zurich, Zurich, Switzerland

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 show that those respondents who live in the vicinity of low quality waterway are willing to pay more for improvements relative to those who live near to high quality waterways.

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

JEL codes: Q51, Q25, Q58

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 employs 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 value 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 benefits 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 (Hanley et al., 2003; Bateman et al., 2006; Concu, 2007). Bateman et al. (2006) provides a review of literature regarding the aggregation of benefit estimates for nonmarket goods. The authors find significant distance decay in values and show that reliance on sample mean WTP can result in bias estimates. This is consistent with the findings of Hanley et al. (2003) who employ contingent valuation and GIS. Concu (2007) is one of the first authors to conduct a distance decay analysis using CE method. The author concurs 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. Martin-Ortega et al. (2009) use CE method via multinomial logit modelling 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 the 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 are estimated. Results indicate that respondents' value the change of water quality significantly more for their respective sub-basins, but only for the highest level of water quality considered. The authors find 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 application employing a random parameter logit model, Condon et al. (2007) examine the influence of respondents' geographical location on values for rural land conservation programs in Florida. The study uses a 20 kilometre (km) radius around respondents and four variables hypothesised to affect individual values which are constructed using a GIS. Results reveal that the share of agricultural land and distance to the coast are statistically significant influences on respondents' values. The authors find that compared to using sample mean values, aggregate values incorporating the respondents' geographic information are approximately 17 percent and 50 percent lower for the highest and lowest valued programs respectively. Comparing this outcome with that of Martin-Ortega et al. (2009) emphasises that the direction of aggregation bias from using sample mean values may not always be apparent *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 incorporation of biophysical data into the valuation process to enhance reliability of welfare estimates.

2. Case Study

Canterbury is New Zealand’s largest region, with an area of 45,346 km^2 and a population of approximately 500,000 (SNZ, 2007). The 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), as have increases in nitrogen and dissolved reactive phosphorous in waterways (Cameron and Di, 2004). There are risks of irreversible damages in some instances as long term consequences, such as land application of animal effluent (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). 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. The region experienced a 260 percent increase in the amount of irrigated land from 1985 to 2005, and some 70 percent of consumptive use of water in the region is for pastoral purposes. Increased irrigation also means increased agricultural production and more intensive use of land.

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’s waterways.[1] The respondent is presented with several alternatives and each alternative is made up of combinations of environmental attributes commonly referred to as policy outcomes. Combinations of attribute and its levels are varied systematically in the alternatives according to experimental design theory. The respondent is asked to indicate the combination of the attributes in an alternative they prefer most.

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 regional

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

water management authorities. 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 tax rates. This payment vehicle is 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 activities such as monitoring and enforcement.

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

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.

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 are shown in *Table 2* and are in accord with the Quantitative Macro Invertebrate Index developed by regional water management authorities.

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.

The third water quality attribute allowed us to value the impact of low-flow conditions. This attribute is 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 follows New Zealand Ministry for the Environment recommendations and the range in levels is guided by flow rate data from the Environment Canterbury website (www.ecan.govt.nz).

A D-optimal fractional factorial main effects experimental design produced 18 profiles which were then randomly blocked into 3 versions of 6 choice sets. Each choice question has three alternatives with the third alternative being a constant base alternative. 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 seeks 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 concludes with household socio-demographic questions. The first and third sections are designed to capture preference heterogeneity that is not captured by the attributes in the choice sets.

A Random Parameter Logit (RPL) model was fitted to the choice data 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 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.

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

After evaluating the results from various distributional functional forms, we follow Hensher and Greene (2003) and opt 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.[2] Five hundred shuffled Halton draws are used in maximising the simulated Log-likelihood function.

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

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.

Table 4: Distribution of respondent's 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

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 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 allowed the testing of the spatial hypothesis that respondents' 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 allowed 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 are 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 allowed 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 are tested by interacting each of the respondents' water quality measures with the cost attribute. The parameters of these variables are then incorporated into the estimation of respondents' WTP for improvements in the attribute relevant to the water quality measure using the following equation:

$$\text{Marginal WTP Attribute X} = -\left(\frac{\beta_{\text{k}}}{\beta_{\text{Cost}} + \beta_{\text{Water Quality Measure}_{rl}\text{*Cost}} \times \text{Water Quality Measure}_{\text{rl}}} \right) \qquad (1)$$

where Water Quality Measure$_{rl}$ = SRG (Very Poor to Very Good), SQMCI (0 to 2,..>7) and 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 which provide more plausible welfare estimates. In this study, equation (1) 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.

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. The mail-out procedure yielded 349 usable responses with an effective response rate of 25 percent.

4. Results and Discussion

All parameters except Flow 3 are highly statistically significant and of the expected signs. The standard deviation parameters for all attributes except Flow 3 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 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 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.

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)
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.

4.1 Willingness to pay 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.

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

Attributes and Water Quality Variables	Inclusion of Local Water Quality WTP ($)			Without Local Water Quality data: Overall Sample Mean WTP ($)
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.

Looking at *Table 6* we can see that respondents' WTP increases as water quality deteriorates. Respondents with low SRG have higher WTP to reduce the risk of getting sick relative to respondents with high SRG. Respondents with low SQMCI scores have higher WTP 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 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 considerably different values. This result suggests that valuing water quality attributes by stratifying individuals based on close proximity to rivers and streams provides more plausible welfare measures than asking respondents the overall qualities of rivers and streams in a region.

5. Policy Implications and Conclusions

The results reported in this paper have important policy implications. Practical application of policies by water resource managers 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 greater attention can be considered. In this study, Canterbury residents benefit most by improving ecological quality of waterways, followed by reducing the risk of sickness and lastly, by reducing the number of months that a waterway is in low-flow. Secondly, by showing that further benefit is gained by targeting relatively lower quality rivers and streams initially. Applying the method developed in this paper, policy practitioners are able to use the estimated values as proxies of benefits to evaluate policy actions across rivers and streams within Canterbury.

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. Respondents' WTP for improvements in ecological quality is affected by the ecological quality of their local rivers and streams. The lower the ecological quality, the higher is their WTP to improve it. Respondents' WTP for fewer low-flow months is influenced by flow conditions in their nearby local rivers and streams. The poorer the flow condition, the higher is their WTP to reduce the number of low-flow months. Respondents' WTP to decrease the risk of getting sick is influenced by the SRG of their local rivers and streams. The lower the grade, the higher is their WTP to decrease the risk of becoming sick.

A significant contribution of this paper is the development of a method to incorporate respondents' local water quality data via GIS in estimating WTP for agri-environmental policy. By including respondents' geographical local water quality data, the analyst is able to form a range of estimates dependent on the specific area 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 bias estimates.

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 staffs are also greatly appreciated for providing spatial water quality data. Any errors in this paper are the authors' sole responsibility.

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