An investigation into the use of experienced utility scores to assess multi-attribute changes in environmental quality.

Chris Batstone[1], Jonathan Moores[2], James Baines[3], and Sharleen Harper[2]

1. Cawthron institute, Nelson, NZ;
2. NIWA, Auckland, NZ;
3.Taylor Baines and Associates, Christchurch NZ.

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Abstract

Much contemporary socio-economic environmental policy evaluation is undertaken using decision utility based approaches such as choice modelling and contingent valuation. In this paper we describe an investigation into the use of the contrasting "experienced utility" concept to assess changes in environmental quality. The research context is the development of a spatial decision support system that discriminates between catchment development options in terms of their effects on the receiving water bodies of urban storm water. We report the outcomes of the application of an expert elicitation process from the risk assessment literature to the trial of a visual analogue method designed to elicit experienced utility scores from consultation workshops to assess the effects of multi-attribute changes to ecosystem services in urban estuaries.

Keywords:

Ecosystem services, experienced utility, expert elicitation

Introduction

Urban planning and associated decision making in New Zealand requires considerations of changes to environmental quality impacted by development processes to be assessed in terms of four well beings – environmental, social, economic and cultural. This paper describes an exploratory process to develop and implement indicators for the social wellbeing associated with the attributes of estuarine water-bodies impacted by urban storm water. The process includes identification of experienced utility as the assessment construct, a visual analogue approach as the data collection vehicle, an expert elicitation process approach to obtaining data, and development of a mathematical model for a validation framework.

The context of this research frames the development of the indicator generation process. It motivates development of a cost effective method that can be extended to multiple locations, and has the capacity for integration with indicators of economic wellbeing. The context is a spatial decision support system (sDSS) that discriminates between alternative urban development scenarios in terms of their effects on urban water bodies by contrasting the values of four indices that correspond with the four well-beings (Moores et al. 2013). The indices are constructed using a composite index method (OECD, 2006). Their precursors are established through the use of a combination of physical and statistical models, and Bayesian Belief Network (BBN) models that propagate changes in catchment attributes over time that influence the biophysical properties of the receiving water bodies.

While the sDSS addresses two receiving water body types, freshwater and estuarine impacted by urban development in catchment level planning units, this paper considers estuarine water-bodies and the related social wellbeing. Social wellbeing indicators are constructed based in five kinds of relationships with the water bodies held by the community. Four of those relationships are defined in terms of water quality categories that reflect enhancements to the ecosystem services provided by the water bodies. A fifth relationship, defined as "sense of place", is a summary, multi-dimensional construct. Together they reflect the provisioning and cultural aspects of human wellbeing proposed by the Millennium Ecosystem Assessment (MEA, 2005).

An expert elicitation process (Burgman, 2005) that employs a visual analogue method (Gould, 2001) has been used to elicit experienced utility scores (EUS) from a broadly representative sample of the community (Kahneman and Sugden, 2005). That information reflects the response of community social well-being to a varying ecosystem service provision by the water bodies under differing water body quality conditions resulting from alternate development scenarios and storm water management regimes.

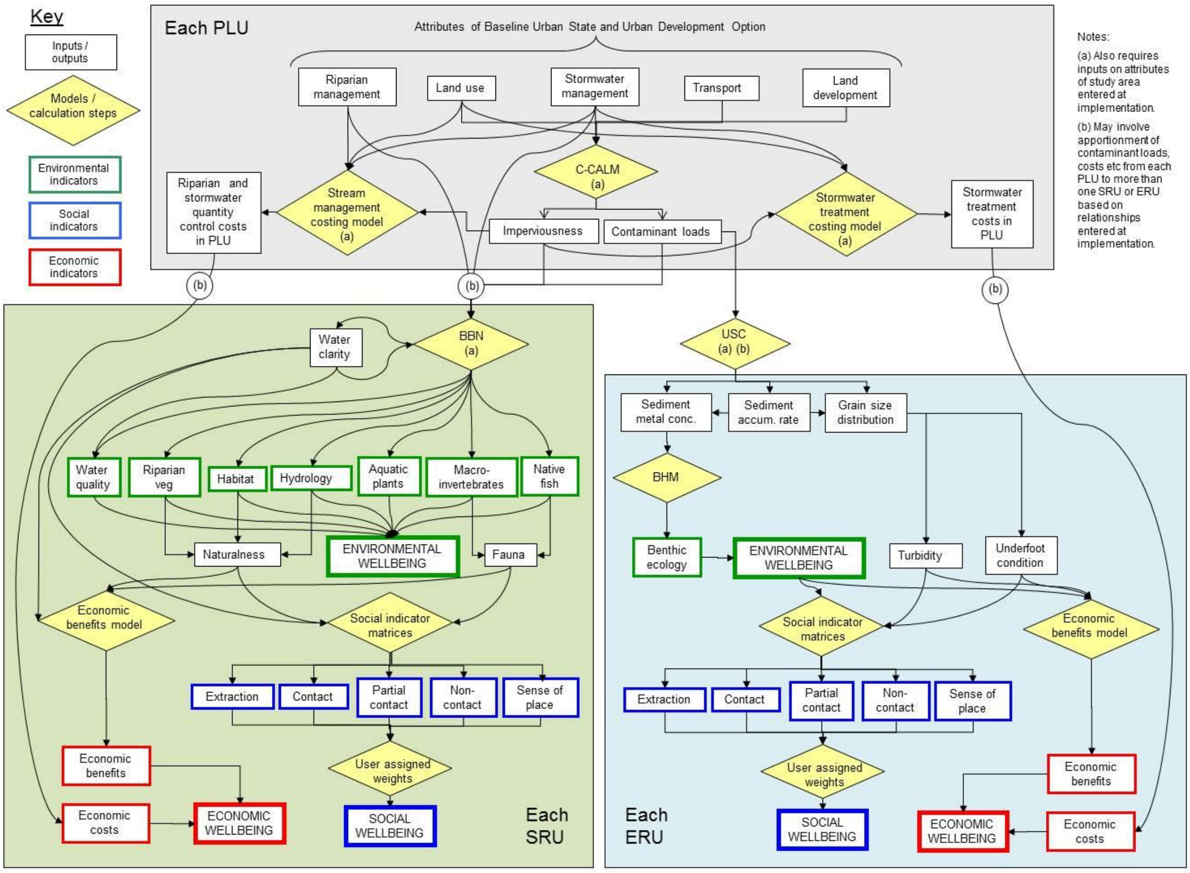
This paper is structured as follows. A research context section provides a commentary on the sDSS, locating the development of a social wellbeing indicator in its decision support software context. A methods section follows that explains the rationale for the method, the construction of the data collection process, and development of a model to validate the data. Presentation of the outcomes of data collection, model estimation and associated commentary are followed by a discussion of the strengths and weaknesses of the method. Concluding remarks provide a summary of the outcomes of this exploratory process with directions for future research.

Methods

The research context

The research context of this paper is a New Zealand Ministry for Science and Innovation funded project entitled “Urban planning that Sustains Waterbodies (UPSW). Figure 1 describes the structure of the sDSS developed in the course of the project. Catchments under consideration are divided into planning units (PLU). Their development status is characterized by a number of executive attributes – riparian management, land use, storm water management, and transport and land development pattern. The flows and associated effects of storm water that arise from varying configurations of these attributes impact a number of stream receiving units (SRU) and estuary receiving units (ERU). For the SRU, those attributes form the starting nodes of a Bayesian Belief Network (BBN) model which uses Bayesian inference to identify the effects of storm water from the PLU into five probability based category determinations for three attributes – naturalness, water clarity, and fauna.

Figure 1: UPSW sDSS structure (Moores at al. 2013)



These three attributes are the basis for defining scenarios under which five human relationships with the water bodies (expressed as categories that reflect incremental enhancements to the levels of ecosystem services available) with the SRU are assessed. For the ERU a number of physical and statistical models are used to model the effects of storm water from the PLU into five category determinations for three attributes – turbidity, underfoot conditions defined as grain size distribution, and ecological health. These three attributes are the basis for defining scenarios under which five human relationships (expressed as categories that reflect incremental enhancements to the levels of ecosystem services available) with the ERU are assessed.

The human relationships with the receiving water bodies are defined as contact, partial contact, non-contact, extraction use, and sense of place. The levels of services available from the water-body impact levels of satisfaction associated with a range of use and non-use relationships which are based in changes to the biophysical / ecological attributes of the resource. Experienced utility scores which vary according to the category levels of their pre-cursor attributes take values over the interval {1 …10}. Similarly people's attachment to a location, their sense of place, is affected by changes to the underlying attributes (characteristics) of the resources. The social wellbeing indicators for SRUs and ERUs are determined as arithmetic weighted averages of the scores for each of the five contributing social indicators for SRUs and ERUs, respectively. Weights are generated through an Analytical Hierarchy Process (Saaty, 1987).

The social wellbeing indicator compliments the other wellbeing indicators by providing an assessment of the state of the resource under differing baseline urban state (BUS) and urban development option (UDO) combinations in terms of satisfaction or utility experienced by the community in their relationships with the water bodies. The economic wellbeing being indicator provides an estimate of the value and efficiency of each development option, the social wellbeing indicator addressed in this paper an assessment of the state of the water-body. Further, it provides an alternate avenue to cost benefit analysis to assess the efficacy and efficiency of alternate storm water management regimes through utility / cost analyses.

The software context of sDSS is Microsoft Excel. Look-up tables contain the data for the calculations that generate the final values for the social wellbeing indicators. Those tables provide information for the three biophysical attributes of ERUs and SRUs, respectively (described above), in five categories. Figure 2 provides an example of a look-up table containing utility data.

Figure 2 portrays a 5x25 cell matrix populated with experienced utility data. Each cell defines a scenario which is a unique combination of three biophysical attributes, each able to take five levels. The numerical value in each cell is an Experienced Utility Score (EUS) obtained from the process described in the subsequent section, Methods. The EUS tend to grow progressively from minimum to maximum values from the left top cell of the matrix to the lower right cell.

The research challenge

The method used to create this indicator of social wellbeing is developed in the context of a software tool. The tool will be deployed in numerous locations that differ in the terms of biophysical attributes and the nature of the relationships held by the community. The tool assumes that the biophysical nature of water bodies at any point in time may be understood in terms of a typology based in three attributes, each attribute taking five levels. The connection with the corresponding socio-economic system is the assumption that human relationships with the water bodies are effectively defined and assessed in terms of the same typology of attributes and levels.

Figure 2: Look-up table example

Underfoot condition	Water clarity	Ecological health				
		low	low/med	med	med/high	high
low	low	1.18	1.55	1.91	2.31	2.71
	low/med	1.58	1.95	2.27	2.64	3.02
	med	1.98	2.31	2.63	2.96	3.32
	med/high	2.07	2.40	2.76	3.18	3.61
	high	2.05	2.43	2.82	3.37	3.92
low/med	low	2.17	2.54	2.92	3.65	4.33
	low/med	2.57	2.90	3.28	4.09	4.79
	med	3.16	3.49	3.95	4.45	5.17
	med/high	3.57	4.12	4.45	4.99	5.51
	high	3.34	3.81	4.21	4.85	5.46
med	low	3.16	3.54	3.92	4.71	5.38
	low/med	3.75	4.13	4.60	5.10	5.66
	med	4.34	4.81	5.27	5.77	6.27
	med/high	4.81	5.30	5.76	6.26	6.81
	high	4.97	5.55	6.26	6.81	7.35
med/high	low	4.89	5.41	5.94	6.41	7.01
	low/med	4.93	5.34	5.72	6.04	6.70
	med	5.37	5.93	6.39	6.89	7.22
	med/high	5.83	6.35	6.89	7.44	7.76
	high	6.22	6.72	7.31	7.85	8.59
high	low	6.47	6.92	7.41	7.91	8.53
	low/med	6.62	7.02	7.42	7.81	8.18
	med	6.74	7.16	7.52	7.84	8.16
	med/high	6.87	7.42	7.94	8.26	8.99
	high	7.00	7.67	8.35	9.09	9.82

The research challenge is to find a parsimonious way of assessing the state of streams and estuaries in terms of the relationships that humans hold with estuaries and streams. An approach is required that identifies changes in wellbeing as the ability of streams and estuaries to provide a range of services changes as urban development effects them. We have adopted the notion of experienced utility understood as satisfaction to address this requirement. The response to the capacity of water bodies to provide ecosystem services is captured as the utility experienced by people in past encounters with alternate water body quality scenarios. Those scenarios are defined in terms of combinations of varying levels of the key attributes of streams and rivers that enable ecosystem service provision. This data reflects how humans feel, think, and how they are motivated to act toward the water bodies as they have experienced them under varying conditions. The use of utility assessment in environmental management is derived from the behavioural and health economics literatures (Hajkowicz et al. 2008). The multi-attribute nature of the process has precedent in Prato (1999). The data collection method has been formulated to provide a multi-attribute assessment method that that minimizes the cognitive loads on workshop respondents.

Community relationships with receiving water-bodies

Five kinds of relationships with each of those water bodies are assessed. Those relationships encompass the components of total economic value (Bateman et al. 2006). Four of the relationships are defined in terms of water quality categories that reflect progressive enhancements to recreation and provisioning ecosystem services provided by the water bodies – non-contact, partial contact, extractive use, and full contact. This typology of relationship categories is based on the water quality ladder concept developed by Vaughan (1986). The water quality ladder features a ten point scale that reflects changes in the character of ecosystem service available as water quality improves. For example, a score of 2.5 represents water quality that is "boatable", 5.1 "fishable", and 7.0 "swimmable" (Van Houten et al. 2007). A fifth relationship, defined as "sense of place" is a summary, multi-dimensional construct that embraces cognitive, affective and conative relationships with the streams and estuaries (Jorgensen and Stedman, 2001).

Experienced Utility

The human – water body relationships are assessed from the perspective of experienced utility or the satisfaction derived from those relationships (Kahneman and Sugden, 2005). This approach is widespread in the health economics domain, but is limited in that it does not offer an opportunity for full integration with cost benefit analysis processes. An example of its application to environmental policy is in the area of water management decisions in Western Australia (Hajkowicz et al. 2008). Tinch et al.(2010) investigated the differences between decision and experienced utility, finding that an experienced utility approach generates different estimates of preferences than those from decision utility, using a choice modelling framework.

The idea of assessing the value of policy options from the perspective of levels of satisfaction experienced in the past by individuals and, by inference communities, is complimentary to the growing trend in the economic analysis of environmental policy to use non-market valuation techniques such as contingent valuation and choice modelling based in the “decision utility” construct which asks survey respondents to anticipate their preferences for alternate scenarios. In the experienced utility approach respondents are asked about their levels of satisfaction, responding from within their experience. In the context of socio-economic analysis of environmental policy the approach has merit in that it avoids two contentious areas. First, the monetization of assessments of environmental value (Kant and Lee, 2004), and second, defining the economic jurisdiction (Bateman et al. 2006) required for aggregation of non-market process derived estimates of value for application to cost benefit analyses. The first of these points provides a rationale for the use of experienced utility to construct the social wellbeing indicator in that it provides an avenue to compliment economic wellbeing indicators based in non-market valuation of losses and gains of ecosystem services. Most importantly however, it may be possible to generalize this tool to a wide range of locations, avoiding the costly necessity to collect data to populate the look-up tables in each and every implementation of the tool, a key factor in development of decision support software.

Visual analogue scores

The data collection methodology to assess experienced utility requires respondents to score the levels of satisfaction they have experienced in their relationships with the water bodies. To capture these scores a visual analogue score matrix has been developed. This a variant on the visual analogue scale (VAS) widely used in the health and allied domains. A VAS is defined as a measurement instrument designed to assess a single characteristic or attitude that is believed to vary across a continuum of values and is not amenable to direct measurement (Gould et al. 2001). In its simplest form the VAS is a line about 100mm long, anchored at each end by contrasting values for the characteristic or attribute under consideration. Respondents are asked to indicate their reply by placing a mark on the line: their score is defined as the distance between the origin (the left hand end of the line) and their mark.
Because the level of experienced utility or satisfaction for each of the five water body relationships is a function of more than one characteristic, the VAS linear scale concept is extended to a matrix in which each cell defines a quality scenario expressed in terms of three attributes, each defined in terms of three levels, low medium and high. Relationships with estuarine water bodies are defined in terms of underfoot conditions, water clarity and ecological health. These attributes were identified in focus groups in a choice experiment

development process for the Waitemata Harbour papered in Batstone et al. (2010). Figure 3 portrays the matrix for estuarine water bodies. Three levels have been used because the literature surrounding non-market valuation emphasizes the potential for anomalous outcomes when the cognitive burden, the complexity of the data provision tasks, becomes overwhelming for respondents (Hensher, 2006). In this application the white coloured cells are available for data collection; the grey coloured cells were deemed unlikely combinations of the attributes and their constituent levels in which minimal distinctions would exist between their utility scores and those in the cells surrounding them. In subsequent data processing non-sampled data points in the matrices are established through interpolation.

Figure 3: Estuary data collection matrix

		Ecological Health		
Underfoot	Clarity	Low	Medium	High
Low	Low			
	Medium			
	High			
Medium	Low			
	Medium			
	High			
High	Low			
	Medium			
	High			

Populating the data collection matrix: eliciting experienced utility data

Data was collected from workshop groups of 20 respondents in Auckland. The method is based in the use of a similar process to collect data for the non-market valuation process used to estimate economic benefits associated with coastal storm water mitigation (Batstone et al. 2010). Workshop respondents were recruited by a commercial market research organization and were paid a fee for their attendance. Given the exploratory nature of this process – the key area of exploration was in the process area - no attempt has been made to provide a strong statistical basis for the inference to the wider population. Within the constraints of a small sample, the composition of these focus groups was designed to be broadly representative of the diversity of populations of Auckland and Canterbury in terms of ethnicity, gender and age. The key recruitment criterion for recruitment to the workshop was experience of at least boating in coastal environments.

Two facilitators coordinated the workshop. A PowerPoint presentation was used to introduce the subject area, and to introduce and to train the respondents in the data collection task. The data collection formats were presented to the group as a whole, respondents made their responses in task specific workbooks which were identical across all respondents. The data collection task was framed as an expert elicitation process based in techniques from the risk assessment and ecology literatures. It aims to minimize the potential for outcomes to be compromised by a range of a range of cognitive biases, for example, anchoring, availability, framing, individual dominance, group think and recall (Burgman, 2005). Data collection involved respondents in a six step procedure to populate a three by nine cell matrix of water body quality scenarios, defined in terms of three levels of three key water body biophysical attributes, with experienced utility scores, for each of the five water body relationships.

Step One: Task definition, and context specification.
Step Two: Training
Step Three: Respondents were asked to locate the cells representing scenarios that corresponded to their best, worst, and most frequently encountered experiences using “happy face” symbols or equivalent, depending on their experience.
Step Four: Respondents were asked to score these key locations based on the degree of satisfaction they recalled experiencing using an interval of $\{1 \ldots 10\}$.
Step Five: Respondents were asked to score the remaining white cells relative to their best, worst, and most frequently encountered scores using the same interval of $\{1 \ldots 10\}$.
Step Six: Respondents were asked to score the reliability of the information they had provided using an interval of $\{1 \ldots 10\}$.

Data processing

Respondent outcomes for each water body quality scenario were aggregated by an arithmetic weighted average scheme in which individual responses were weighted by their reliability score to form representative experienced utility scores for each water body quality scenario. Responses with a reliability score of less than 0.8 were excluded from further processing, based in the Cronbach’s Alpha statistic’s standard for internal consistency (George and Mallery, 2003) as a reference point. Initial data processing filled in values in the 3x9 cell matrix using an interpolation scheme that related column values through identification of power relationships for the sequence cells which held data.

Final processing of the scores used a surface interpolation process to expand the water body quality scenario cell matrices from the three by nine cell matrices of the data collection workshops to five by fifteen cell matrices to create correspondence with biophysical attribute precursors in the sDSS. The expansion of the tables was affected using a predefined MATLAB routine called TriScatteredInterp which performs linear interpolation on an irregularly spaced three-dimensional grid (MATLAB, 2012).

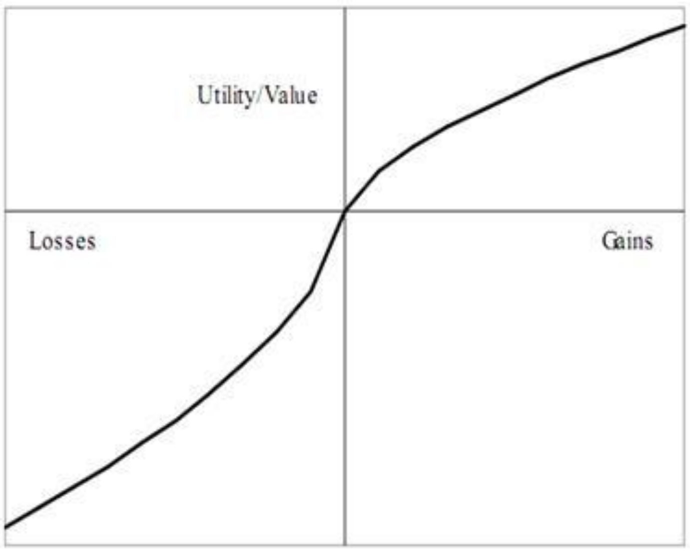
Validation

In order to validate the data collected for the sDSSS we estimate value functions at the level of the individual, and at two stages of data processing. Two aspects of economic theory have relevance, Prospect Theory and Utility Theory. Prospect Theory (Kahneman and Tversky, 1979) suggest that at the individual level, people make decisions based on losses and gains rather than the final outcomes, those losses and gains relate to some reference point, and that they use a variety of heuristics to obtain those outcomes. The definition of the reference point is not trivial, its location is critical to specification of empirical value functions that demonstrate the “S” property While the status quo is often taken as the reference point, Kahneman & Tversky (1979) recognise that reference points may be influenced by other factors. A number of other studies (Suls & Wheeler, 2000; Pervin, 1989, Frederick & Lowenstein, 1999) have examined aspects such as social comparisons, subjective expectations and past experience, Camerer and Loweinstein (2004) conclude that how multiple reference points are combined is still an unanswered question.

Since we have requested respondents to indicate the most often encountered water-body attribute combination scenario there is a reasonable expectation that the individual value functions are “S” shaped: concave in gains, and convex in losses in relation to the reference point.

A number of functional forms are available to test this feature. Carter & McBride (2010) test power regression, spline regression, and polynomial functional forms, in particular 3rd degree polynomials to demonstrate the presence of an “S” shaped value function in experienced utility data. Those authors cite Luce (2000), noting that on aggregation the “S” shape is not always evident. While a number of studies have been able to establish the “S” shape, (Galanter, 1990), Vendrick & Woltjer, (2007) and Layard, Mayraz and Nickell (2008) report concave value functions. This is consistent with utility theory that suggests value functions reflecting preferences for bundles of goods and services are continuous (on the assumption that they are transitive and complete), feature diminishing marginal utility, and are therefore concave in shape (Carter, 2001).

Figure 4: Prospect theory “S” shaped value function (Source: Carter & McBride, 2010)



To assess the presence of an “S” shape in each of the data forms we use OLS regression to test whether a 3rd degree polynomial may be fitted to the data. If that test fails, then we investigate whether a power function reveals a concave relationship between utility and each of the attributes. In order to address the multi-attribute, multi-level nature of the data we have taken the following approach to assessing power form relationships.

Let U = utility, and A, B, and C are environmental attributes, each with five levels where U is defined by the following general model:

$$U = f(A, B, C) \quad \ldots (1)$$

In the absence of information about the power form of the relationship between utility and each attribute, and assuming a multiplicative relationship between each of A, B, and C gives,

$$U^z = A^a B^b C^c \quad \ldots (2)$$

Where, z = 1 to 5 is the community-water-body relationship type and a, b, and c are coefficients to be estimated from the data. Further, z =1 represents the non-contact relationship, z=2 the partial contact relationship, z=3 the contact relationship, z=4 the extraction use relationship, and z=5, the sense of place relationship. This functional form allows for interaction between the attributes in the formation of experienced utility allowing the data to "speak for itself".

In stochastic form equation (2) becomes:

$$U^z = k\, A^a B^b C^c + u \quad \ldots (3)$$

Where,

k is a constant term and *u* is the stochastic disturbance term.

In order to make equation (2) tractable for estimation using ordinary least squares (OLS) regression it is necessary to log transform the data to achieve a linear form:

$$\ln U^z = \ln k + a \ln A + b \ln B + c \ln C + e \quad \ldots (4)$$

Where, *ln* represents the natural logarithm operator, and *e* is the residual term.

Allowing A = UC, B = water clarity, and C = ecological health, then equation (4) becomes,

$$ln(U)_i^z = \ln k + a \ln UC_i + b \ln WC_i + c \ln EH_i + u_i \quad \ldots (5)$$

Two tests may be performed to demonstrate consistency with a priori expectations in respect of diminishing marginal returns. First, the coefficients a, b, and c are statistically significantly different from zero. Second for the concave relationship to hold the estimated coefficients (a, *b*, *c*) lie in the interval {0 … 1} such $0 < a < 1$; $0 < b < 1$; and $0 < c < 1$;

In order to estimate equation (5) continuous variables representing the environmental attributes were developed from the attribute category data, with the category levels assigned integer values of 1 to 5 corresponding to the scheme 1=low, 3=medium, and 5=high based in the assumption of equal intervals between the categories. The order of the observations in the workshop and look-up table datasets was randomized to remove serial correlation effects arising from collection and interpolation processes.

Results

In this paper we use data collected from the workshop addressing the sense of place water-body relationship to illustrate application of the concept and the methods we trialled.

Graphical analysis

It was not possible to fit 3rd degree polynomial functions to the aggregated data.

However, at the individual level we find that the shape of the value functions evident range from clear depictions of the "S" shape, to concave forms of the 3rd degree polynomial. Figure 5 describes an instance of a workshop response clearly displaying the "S" property; Figure 6 a sample of workshop responses ranging from "S" to concave.

Figure 5: Workshop data "S" shaped value function response example

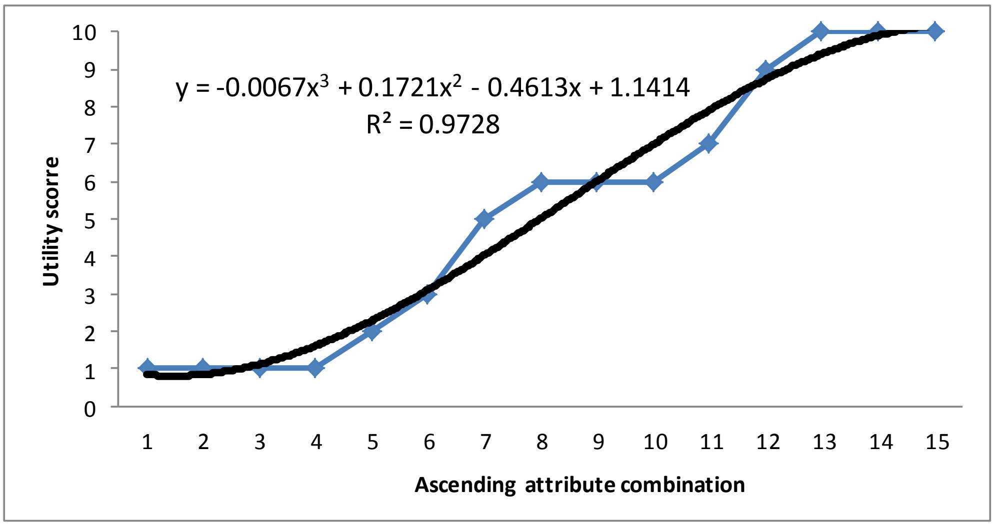
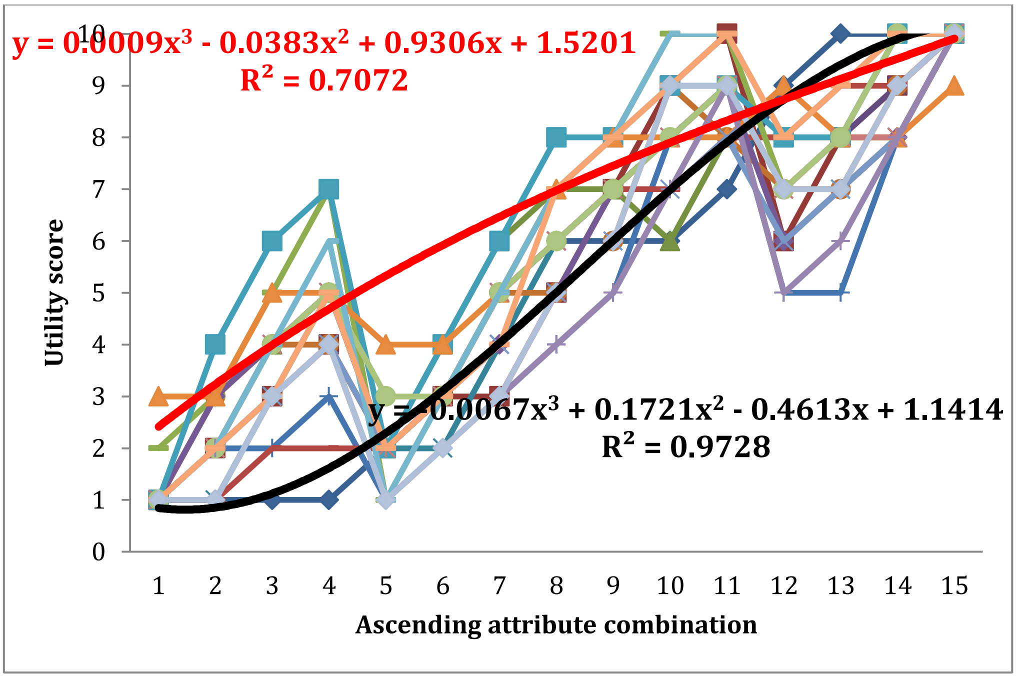


Figure 6: Range of workshop data responses: "S" shape to concave



The evidence is mixed as to the presence in the data of "S" shaped value functions amongst the individual workshop responses. Those that deviate most from this standard at least exhibit the concave shape required by the presence of diminishing returns.

Model estimation

Twenty models of the functional form described by equation (5) were estimated using OLS from the workshop and look-up table data. The twenty models derive from there being ten relationships (five coastal and five freshwater) between utility and the environmental attributes, each of which are explored in two datasets. These two datasets were: values generated in workshops (workshop data) and by interpolation based in the workshop data (look-up table data).

Table 1 describes the estimation outcomes. For the workshop data sets based on 3x9 cell tables n=27, for the look-up table data sets based on 5x25 cell tables, n=125. In each table the coefficients estimated from the workshop data and look-up table data are presented for each relationship model.

	Attribute					
Model	Underfoot conditions		Water clarity		Ecological Health	
	Workshop data	Look-up table data	Workshop data	Look-up table data	Workshop data	Look-up table data
Non-contact	0.5976	0.7130	0.3060	0.1963	0.8151	0.2630
Partial Contact	0.4863	0.5481	0.2715	0.1693	0.7277	0.2690
Contact	0.5788	0.6435	0.2924	0.1837	0.8247	0.2927
Extraction	0.6374	0.5921	0.2446	0.1679	0.9054	0.4368
Sense of Place	0.6090	0.6991	0.3112	0.2006	0.8469	0.2931

The explanatory power of each of the models is high, ranging from Rsq= 0.85 to 0.95 over the twenty models in the analysis. Correlation analysis shows that that the explanatory variables in the models are uncorrelated. Consideration of the values obtained from estimation for the Durban Watson statistic show the randomization process has removed any serial correlation issues that would compromise assessment of the statistical significance of the estimated coefficients or create bias in their magnitude. Plots of the residuals do not show evidence of any patterns associated with heteroscedasticity.

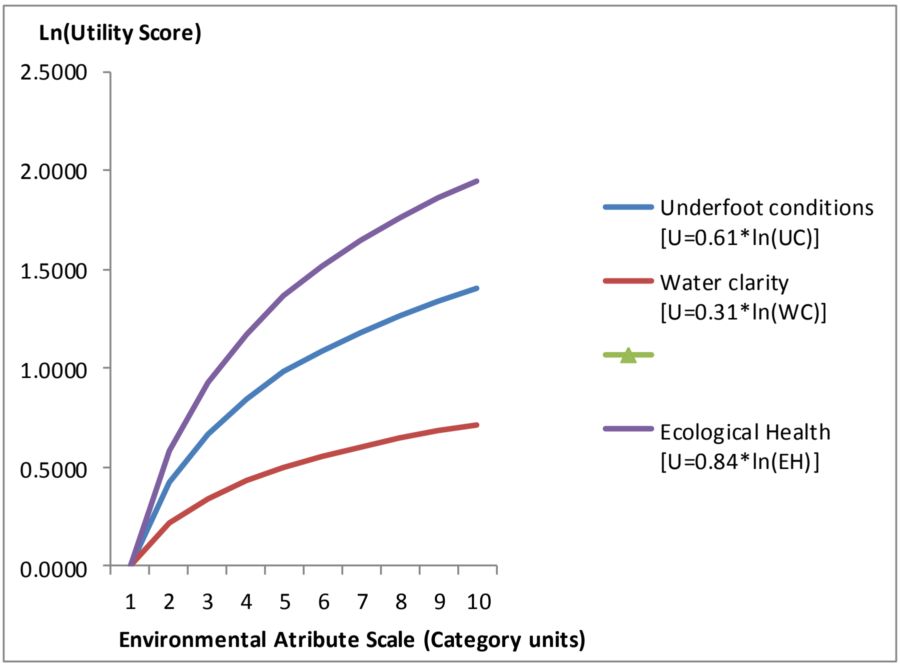
As the model variables are in log-log form, the coefficients may be interpreted as a 1% change in the environmental attribute is associated with the coefficient value percent change in experienced utility. For example a 1% improvement in the water clarity attribute is associated with a 0.2488% improvement in experienced utility associated with sense of place in freshwater workshop data.

The estimated coefficients are all statistically significant at least at the 5% level. The statistical significance of the coefficients and their magnitudes confirm the relationship between utility and each of the environmental attributes that reflects diminishing marginal returns, *ie* demonstrating concave shape value functions in the aggregate data.

There are some inconsistencies in the relative magnitude of the coefficients between workshop based data and the interpolated data that be indicative of the interpolation process not preserving the underlying characteristics of the data, and / or there may be some more fundamental issues with construction of the data collection vehicles.

Figure 7 depicts an example of those relationships using the coefficients for the sense of place model estimated from the aggregate workshop data.

Figure 7: Expected utility response to increasing levels of environmental attributes



Discussion

The UPSW sDSS operates by defining the biophysical state of a water body in terms of a typology consisting of three attributes each specified by five levels. Look-up tables contain data that specify the average level of utility experienced by the community for relationships with the water body for each biophysical state. To determine the effects on social wellbeing that arise through urban development the tools contrast the levels of experienced utility contained in the look-up tables for the current state of the water body and the state predicted by models for the end point of development.

Prior to the 20th century the utility concept was understood as a Benthamite hedonic calculation that resulted in the net of pleasure and pain, with research effort to develop measurement of the concept. Thereafter followed a shift in thinking (Robins, 1932) that took the view that he hedonic qualities could not be measured, and that interpersonal comparisons were invalid. Since utilities could be conceived as consistent choices through revealed preferences the pursuit of the measurement of utility was held to be redundant (McBride & Smith, 2010).

The work of Kahneman and Tversky (1979) and their development of Prospect Theory signalled renew interest in utility. Drawing on the psychology literature Kahneman et al. (1997) assert that "experienced utility is measureable, and that the differences between decision utility (wanting) and experienced utility (enjoying) is important for understanding behaviour, and in turn the design of public policy (McBride & Smith, 2010).

This research has adopted an experienced utility approach to the development of a social wellbeing indicator because it is complimentary to economic approaches based in decision utility in understanding the effects of alternative urban development approaches on the extent of ecosystem services accessible by humans. In the context of the sDSS, the experienced utility scores allow specification of the state of ecosystem services, reflected in experienced utility. In contrast, decision utility based assessments of the economic value of gains and losses from processes such as contingent valuation and choice modelling give depictions of the value of the change. The use of experienced utility scores as the information base for the social indicator compliments the sDSS information basis, providing two socio-economic indicators based in differing cognitive processes. Psychologists understand there is a significant difference between the two, known as the focussing illusion (Schade & Kahneman, 1998) by which decision utilities overstate post-decision experienced satisfaction.

Kahneman et al. (1997) argue that in contrast to the mainstream neoclassical view, experiences of temporally extended episodes are measurable because "they relate subjective intensity to physical variables that are qualitatively similar for different people"…. and that "reported subjective intensity is often a power function of physical magnitude, with an exponent that varies for different sensory dimensions" (Kahneman et al. 1997:380).

While Schade and Kahneman (1998) provide a justification in the focusing illusion to seek a diverse and complimentary information basis to understand changes in ecosystem services, Kahneman et al. (1997) provide the substantial foundation for the use of data based in the experienced utility from temporally extended episodes (the actions that form the basis of the five relationships with water-bodies) and the use of power functions (equation 2) to form the basis for a functional form for a value function that relates experienced utility to multi-attribute changes to water-bodies that result in changes in ecosystem services.

Making the experienced utility concept operational involves identifying an appropriate sample, identifying a framework for data collection and a mechanism to populate the framework, and developing and testing a mathematical model of the experienced utility for contrasting states of water body. Given the exploratory nature of this research, and while the sample selected is broadly representative of the Auckland region, it is small for statistical inference purposes. Accordingly caution should be assumed when making inference from the data described here.

The analysis recognizes the statistical weakness that lies in the small underlying sample sizes that are the data sources, but also recognizes that expert elicitation techniques are designed to operate with small samples. The statistical model estimation process that constitutes the validation analysis has been conducted over data sets that are based in small original sample sizes, and have been conducted over data that has been created from interpolation to impute missing values. With these reservations in mind the following is relevant. Given that it is possible to fit models of high explanatory power with highly statistically significant parameters, this validation analysis shows that the data in both the 3x9 and 5x25 cell tables follow an underlying model that has econometric precedent, and that they demonstrate the presence of diminishing returns that is the expected feature of utility data. Accordingly there is reasonable evidence to accept the data and associated processes and to proceed to identify and remedy issues that arise in the data collection, and data processing.

The data collection process needs to be reconsidered to eliminate any order effects that may arise from the construction of the data collection tables. Block designs or randomization of table formats could be considered. Potentially software such as Ngene that is used to specify choice experiment formats could be used to establish formats with minimum sample sizes. Accessing a larger sample from the community would improve representativeness and potentially the reliability of the data. Presentation of information in the data collection tables should be modified so not to lead respondents. Consideration should be given to alternative labels for the levels of the attributes other than of high, medium and low.

The expert process employed to elicit data could be reviewed: the approach taken in this research has only partially implemented processes advocated by Burgman (2005) in that respondents were not presented with aggregate results from the workshop, then offered the opportunity to update their own individual data as in Delphi approaches. The interpolation process enacted to complete the workshop data tables and to expand that data to the final look-up table format should be reviewed in order to preserve the information in the workshop tables. In validation processes the variables representing the attributes should have a foundation in real data, rather than integers that represent categorical variables as has been used in this analysis.

Conclusions

In this paper we have described the application of experienced utility in various forms to assessing changes in wellbeing associated with changes to attributes of estuarine water-bodies that in turn determine the level of ecosystem services available. In particular we report the application of a visual analogue method which employs expert elicitation techniques tot eh task of collecting experienced utility, and projected experienced utility data. Using validation approaches based in Prospect Theory and more conventional utility theory we shown our data demonstrates features required of utility data – "S" shaped, or at least concave in individual data, and concave in aggregate data. We note avenues to improve data collection, and to refine post data collection processing.

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