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Reducing gain–loss asymmetry: A virtual reality choice experiment valuing land use change

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ABSTRACT

In the majority of choice experiments (CEs) the attributes of non-market goods are conveyed to respondents as a table of numeric and/or categorical data. Recent research suggests that respondents may have difficulties evaluating data in this format. In the context of a CE eliciting preferences for changes in coastal land use, this study uses a split-sample experiment to compare standard presentations with virtual reality (VR) visualisations conveying objectively identical information. We find that compared to the standard presentation, preferences elicited in VR treatments are less variable and exhibit a significant reduction in asymmetry between willingness to pay (WTP) for gains and willingness to accept (WTA) for corresponding losses. We conjecture that the greater 'evaluability' of the VR presentation reduces respondent judgement error and moderates reliance on the loss-aversion heuristic.

1. Introduction

Economic theory postulates that an individual's choices regarding trade-offs between goods will be dependent upon the attributes and services of those goods and the characteristics and preferences of that individual [36]. However, given the virtually infinite variety of goods and provision changes which could conceivably arise, it would clearly be both highly inefficient and practically infeasible for individuals to invest time in determining prior preferences for all options. Indeed, the existence of *prior* preferences is not required by economic theory [13]. Rather it is assumed that individuals form their preferences as required and in response to the information provided regarding the goods in question. As Munro and Hanley [46] highlight in their review of the issue, information plays a key role in the formation of preferences, particularly for the valuation of non-market goods where experience of the good and any hypothetical market may be low. However, as Green and Tunstall [20] emphasise, accurate and 'face-value' comprehension of the information provided within non-market valuation studies cannot be taken for granted.

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While many non-market valuation manuals focus strongly upon the accuracy of information provided to survey respondents (e.g. [3]), an increasing concern is the comprehension [44] or 'evaluability' of that information [28]. Here the argument is that, unless individuals connect with and understand a piece of information then it will (at least to some degree) lack meaning [4]. Interestingly, an individual may on an objective level be able to acknowledge that one numeric value is larger than another, but in the absence of evaluability this information will lack meaning. Psychological insights into this issue suggest that, in such situations individuals may 'construct preferences' using a variety of decision heuristics or 'rules of thumb' [49,54]. Evidence of such preference construction has been observed in a number of experimental and non-market valuation studies (see, for example, [2,21]), resulting in responses which are, from the perspective of standard economic theory, anomalous and unsuited for incorporation within decision-making.

Evaluability is therefore key to avoiding anomalies in stated preferences. With regard to the issue of information provision there is a growing consensus amongst best-practice guides that the most effective route for promoting such comprehension is via the use of visual stimuli [35,44]. This conclusion draws in part upon a substantial, longstanding and ongoing literature showing that the presentation of information in visual form can, in many situations, greatly enhance its evaluability. Early findings include the work of MacGregor and Slovic [40] who show that visual displays outperform conventional information in terms of respondents being able to correctly assess factual outcomes. More recently Lipkus and Hollands [38] show that visual information outperforms numeric data as a basis for the accurate comprehension of risk. Indeed the evaluation of health care risks has provided a number of examples where visual information has consistently outperformed equivalent numeric information as a route for minimising perception and judgement errors. For example, Hibbard et al. [26] found that individuals asked to pick the best health insurance plan from an array of satisfaction ratings chose an inferior plan 45% of the time. However, the simple addition of visual information reduced error rates to only 16%.

Such findings therefore suggest that an important strategy for reducing anomalies within non-market valuation studies may be the use of visual information for describing the good concerned. Certainly many applications of the contingent valuation (CV) method rely heavily upon visual stimuli to convey the single valuation scenario they are concerned with (see, for example, [12]). However, recent years have seen a rapid expansion in applications of the choice experiment (CE) method wherein survey respondents are presented with a series of choice tasks where they make repeated trade-offs between different specifications of a non-market good and alternative prices. A potential evaluability problem here is that while applications may well introduce the general issue using accessible, often visual, stimuli (for example by showing survey respondents pictures of a land area which is going to be affected by some policy), the actual choice questions from which valuations are derived are almost always presented as a series of numeric levels for each of the attributes which define the good. Given the previously discussed work on evaluability it seems likely that many respondents find these numeric levels difficult to comprehend. To illustrate this point, consider the following examples of attributes and their levels used in certain recent CE studies:

- choosing between land use options including, amongst other attributes, the area of teatree woodlands and the amount of vegetation along rivers and in wetlands, both measured in hectares [42];
- the number of metres per kilometre of dry stone wall field boundary which would be restored under an option [16];
- changes in the population of wild geese [23];
- the percentage of lake acres and river miles with good water quality [41];
- asking respondents to choose between options defined by differing areas (in hectares) of urban, sugar cane and 'rare or unique vegetation' land use [43];
- textual descriptions of scenery along a recreational trail [37].

In each of these studies numerous other attributes completed the description of a choice option and, compared to those listed, those other attributes (e.g. the cost of an option) may be much more readily evaluable.

What are the likely consequences of presenting the levels taken by a given attribute in a poorly evaluable manner? The psychological literature discussed previously makes a clear prediction; unable to easily evaluate the information, respondents will be liable to larger and more frequent errors of judgement in assessing the (dis)benefits that an attribute provides. Of course, individuals are more than aware of the difficulties they face in processing poorly evaluable information and, as such will perceive their judgments regarding the (dis)benefits of that attribute as being imprecise. The existence of such uncertainty may trigger what is arguably the strongest and best-documented of all heuristics: gain/loss asymmetry. In particular, an ambiguity-averse respondent will tend to undervalue the potential benefits of an uncertain gain whilst overvaluing the potential disbenefits of an uncertain loss [10].

The tendency for people to strongly prefer avoiding losses rather than acquiring gains is, according to a recent review, the most intensively experimentally investigated of all economic phenomena [27].[1] Standard economic explanations of gain/loss asymmetry focus upon income and substitution effects [22], although Sugden [50] argues that it would take

[1] Pertinently, Horowitz and McConnell find that the less a good is like an "ordinary market good" then the higher is the degree of gain/loss asymmetry. Given that the present study examines an environmental non-market good we should not be surprised to find substantial asymmetry within our resultant valuation estimates.

implausible levels of income and substitution effect to generate the degree of asymmetry observed in empirical studies. In contrast, psychological critiques contend that a major driver of this phenomena is the 'loss-aversion' heuristic [34,55]. A possible explanation of loss aversion follows the discussion above. Here imperfect comprehension of, or uncertainty regarding, a good will both increase valuation variability and drive up the amount which ambiguity-averse individuals demand in compensation for a loss of that good relative to the amount they are prepared to pay for gains of that good.

The above discussion motivates our study. Insights from studies of information comprehension suggest that conventional, numeric descriptions of certain attributes within CE studies of environmental goods lack evaluability. This is liable to exacerbate judgement errors, raising the variability of responses and leading survey respondents to resort to heuristics (such as loss aversion; the focus of our study) to formulate responses. Such strategies would in turn raise measures of willingness to accept (WTA) compensation for losses relative to willingness to pay (WTP) for gains. The same literature suggests that visual representations of these attributes may enhance their evaluability, reducing response variability and dependency upon the loss-aversion heuristic and hence decreasing (if not removing) the asymmetry between WTP and WTA measures.

Recent advances within the field of virtual reality (VR) visualisation have opened up the possibility of directly addressing the evaluability critique of CEs by visualising the attribute levels which comprise each choice option. This paper draws together these techniques to develop a new valuation methodology, the virtual reality choice experiment (VRCE), which relies upon visual information to present complex environmental changes to individuals. In so doing this research combines the notion of 'evaluability' with the wider theory of 'naturalistic decision making' (see, for example, [47]) which stresses the importance of including wider and more natural context within decision making. Fiore et al. [18] argue that one of the major benefits of a VR-based approach is the incorporation of such context, allowing a move away from the highly focussed and abstracted environment of the typical economic experiment.[2]

In the following section we describe an experimental design to implement such a study. This concerns changes (both increases and decreases) in various types of land use within a specified area. The study employs state-of-the-art VR software to generate visual representations of environmental land use change options seen by a sample of CE participants. A split-sample approach is used to contrast the choices of the latter group with those of a second sample faced with a conventional CE design in which objectively identical information is presented in numeric form. A third treatment is constructed by presenting a further sample with both the visual and numeric information. All respondents view the same full factorial design which allows for both gains and losses of each land use type and thereby the estimation of both *WTP* and *WTA* values.[3] Contrasting these measures across treatments allows inspection of the degree to which the gain/loss anomaly occurs and is ameliorated or exacerbated by the differing modes of information provision. Subsequent sections describe our empirical results and present discussions and conclusions.

2. Study design: attributes, virtual reality visualisations, hypotheses and empirical modelling

2.1. Attributes

Given the above concerns regarding the evaluability of attribute and levels, we decided to focus upon one of the most common application areas within the field of environmental valuation; land use change. Such subject matter is in principle highly suitable for both numeric and visual presentation of information. The land use change issue is also ideally suited to the use of both increases and decreases in attribute levels as land is employed between different uses.

A convenient case study issue presented itself in the form of an ongoing debate concerning management of the North Norfolk (UK) coast and in particular the coastal area at Holme. This low-lying site consists of a mix of two types of non-commercial land use: freshwater nature reserve (which we subsequently denote '*Reserve*') and mudflats which are flooded at high tide ('*Flooded*'), the remainder of the area being farmed.[4] The allocation of land uses in the area is primarily determined by the degree of protection afforded by a series of man-made coastal defences. A number of policy options are being actively considered by relevant authorities [32] which means that a plethora of trade-off possibilities exist between these land uses and defence expenditures (the final '*Cost*' attribute). However, our prior expectation, based in part upon preparatory focus group work [33], was that respondents were likely to want increases in the *Reserve* area and decreases in *Flooded* land (while of course seeing increases in *Cost* as decreasing utility).

[2] The significant role of context has been demonstrated in many economics analyses (see, for example, [14,24,9]).

[3] To date a small number of studies have investigated and confirmed WTP/WTA asymmetries within a CE setting including an analysis of food attribute demand [29] and choice amongst travel routing options [25].

[4] Arguably stated preferences over land use and expenditure options could be influenced by values for changes to agricultural area. While this seems unlikely (given the long standing surplus of agricultural land), to allow for the possibility (and reinforce the notion that the overall study area is constant) the residual farmed areas were presented to respondents as part of each choice option. Note that this does not constitute a further CE design attribute as agricultural land area is always the difference between total area and the sum of the *Reserve* and *Flooded* area. As such, in modelling preferences we take agricultural land as the default land use; preference parameters reflect the values for gains/losses in *Reserve* or *Flooded* area when those changes entail the contraction/expansion of agricultural land.

2.2. Creating virtual reality visualisations of land use attributes

The notion of using visual images within valuation studies is not a new one. Previous studies have employed a range of visual cues including artists' impressions, maps, and computer-edited photographs and photomontages [19,56]. As an extension of the latter approach, a limited number of applications have used computer-generated two-dimensional, still images to convey built environment design elements [15]. However, beyond the field of valuation research, ongoing advances in computing power have allowed the analyst both to consider a more varied array of landscapes, and to bring in features such as three-dimensional representation, image animation and user interactivity. Analysts have also introduced routines to allow individuals to choose between scenarios (e.g. [8]). Further recent development in the export capabilities and plugins available in conventional geographical information systems (GIS) such as ArcView and MapInfo, has generated a new generation of VR-GIS capable of interactive landscape visualisation (e.g. [30]). Most recently systems such as those manufactured by SGI [48] and Evans & Sutherland Ltd. [17], and software such as that from Multigen-Paradigm offer the opportunity to freely explore and interact with virtual worlds in real-time. Increasingly there is the capacity to base those virtual environments upon real-world, spatially referenced GIS data, for example via packages such as Terra Vista [52]. It is this VR-GIS approach which we adopt in the present study.

In order to ensure that the options presented to respondents within a subsequent CE exercise were grounded in the reality of the study site, an initial analysis of the physical characteristics of the area was undertaken. Here a GIS was used to employ methods developed by Jude et al. [31] to modify Ordnance Survey (OS) Land-Line.Plus 1:2500 scale vector line data and produce a baseline digital map of the area. This allowed the researchers to examine possible land use change in the area under a matrix of flooding and flood defence scenarios (details given in [32]). This analysis identified an area of some 274 ha where a continuous trade-off between the *Reserve*, *Flooded* and *Cost* variables was possible. This therefore constituted an ideal study area for our CE analysis.

In order to enhance the policy application of results, rather than 'invent' future virtual environments these were generated from data concerning the real-world physical characteristics of the study area. To achieve this, the GIS was used to combine our baseline digital map with various other OS data resources including a digital elevation model representing the study site's topography (OS Land-Form Profile, OS Land-Line.Plus and OS Meridian) and large and medium scale line data edited and classified to provide a landcover map of both the study area and surrounding land to which textures representing changes in land use could be applied.[5] This allowed the data-driven definition of a variety of future land use scenarios, all of which were within the bounds of possibility dictated by the natural characteristics of the case study area. VR representations of any given land use scenario could then be produced by importing the GIS data into a series of linked VR and imaging packages.[6] Some minor enhancements were added to further improve the evaluability of the VR images such as adding a grey-tone shading to areas beyond the study area to clarify that they would remain unchanged. The resultant 'interactive' VR images permitted viewers to 'fly-through' the virtual environments created taking whatever path and altitude they desired, landing at will and moving across the surface of the *VR* area. For illustrative purposes, Fig. 1 presents images from both the status quo and various alternative scenarios taken from various viewing points.[7]

One of the advantages of the design approach taken was that, once created, the VR environments could be readily exported to and run on conventional PC machines. This greatly enhances the potential for such applications to enhance the participatory decision-making process [1]. However, for experimental purposes allowing subjects freedom to determine their own investigation of each VR environment seemed likely to lead to individuals taking substantially different lengths of time to complete each choice task, potentially weakening the comparability of responses. Therefore, pre-set flight paths were used to describe the options in each choice task.[8] In conditions where experimental rigour is not an issue such a requirement could readily be relaxed.

2.3. Design

Real-world current levels were used to define the status quo for our two focal land use attributes, *Reserve* and *Flooded*. In order to allow for non-linear (and potentially asymmetric) preferences across both the gain and loss dimension, we required a minimum of four levels for each of our land use attributes; two of which had to be increases over the status quo and the other two being decreases (each representing roughly similar proportional changes across the two attributes). Combining the four levels of both of the land use attributes plus the status quo gives a total of 17 possible land use

[5] Note that there were no buildings within the study area, however those nearby were identified using OS Address-Point data and three-dimensional VR building models attached so as to enhance the realism of the resultant VR images, i.e., survey respondents were able to see beyond the study area to view realistic landscapes.

[6] These include Terrex Terra Vista, MultiGen ModelBuilder3D, Audition Virtual Reality Viewer software, Bionatics REALnat and Adobe PhotoShop. Details are given in [31,32].

[7] Representing such images within the confines of a two-dimensional page is less than ideal. However, higher quality still images are available at http://www.uea.ac.uk/~e154/research/visualisations/ while a film of a respondent completing a shortened version of the questionnaire (including an abbreviated version of a fly-through) is available at http://vrlab.env.uea.ac.uk/e154/choiceexperiments/.

[8] This was achieved via a simple Visual Basic program which delivered controlled viewing of pre-set fly-through files to participants using Quantum 3D Audition VR viewer software.

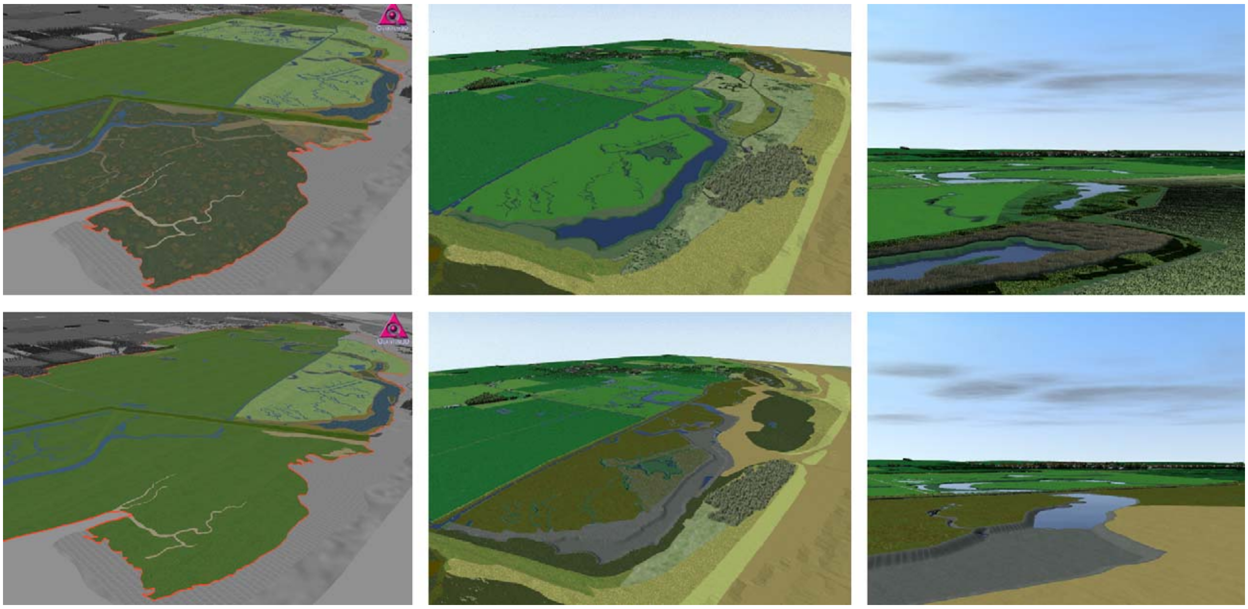

Fig. 1. VR visualisations of the status quo (upper row) and various alternative land use scenarios (lower row) from different viewing points.

permutations within the study area, each of which required a VR visualisation in order to be entered within our survey design. These visualisations were generated as discussed above. The levels for the *Cost* attribute were derived from a pilot CV exercise (described in [33])[9] which also successfully tested out the payment vehicle, this being changes in water utility bills.

Combining the four levels for each of the *Reserve*, *Flooded* and *Cost* attributes dictates a full factorial design of 64 options. These were incorporated within a simple binary SQ+1 question format in which each choice is between the status quo and a single, randomly selected option. In order to further reduce cognitive load, each experiment participant faced a random draw of 16 choice tasks from the full factorial.

The delivery format and introductory sections of the survey instrument were identical for all respondents. A computer-based survey was designed to administer the survey,[10] with participants viewing information and making their responses using a standard desktop PC in an experimental laboratory with all participants isolated from each other. The survey questionnaire comprised of several sections and was designed to be largely self-administered following some initial introduction by the session facilitator (together these conditions greatly enhance the transferability and dissemination of such approaches). A set of introductory pages outlining the survey and how it worked were followed by a description of the land management issues at the study site, and its characteristics. These included a series of photographs and maps as visual aids introducing the site and its attributes. Photographs of the *Reserve*, *Flooded* and agricultural areas of the study site were then presented to all participants so as to mimic the standard introductory information used in most good-quality valuation studies. Fig. 2 presents an example of this information, in this case showing the status quo location of agricultural land within the study area together with a photograph of this land type taken in-situ. Similar information was presented for the *Reserve* and *Flooded* attributes and a colour paper map of the site and its land uses under the status quo situation was also given to all participants from the outset of the experiment. Participants were then asked a number of simple 'warm-up' questions regarding their usage, perceptions and attitudes toward the North Norfolk coast.[11]

Once the base map and photo-information was delivered to all participants, unbeknown to those subjects, the experiment then divided into three treatments to which respondents were randomly allocated. These were devised to examine the hypothesised difference in gain/loss asymmetry arising from the use of visual as opposed to numerical information. In the first treatment, denoted *NUMERIC*, the CE choice tasks faced by participants were presented in standard

[9] Details of attribute levels are as follows: for *Reserve* the levels were 0, 43, 112 and 149 ha with a status quo of 93 ha; for the *Flooded* attribute levels were 0, 12, 95 and 125 ha with a status quo of 30 ha. For the *Cost* attribute, levels were bill increases of £1, £5, £10 and £30 per annum (with appropriate text clarifying that those who paid water bills as part of their rent would still face these increases). We chose not to postulate reductions in bills as our previous work suggested that this might lack credibility [7]. Rather utility gains in one good are balanced by a mix of (where appropriate) increases in bills and/or losses in the other good (as per the good–good trade-offs used in [6]). However, all utility changes (both gains and losses) can be expressed in monetary terms through the inclusion of the *Cost* attribute within our design.

[10] The survey was written using HyperText Markup Language (HTML) and made extensive use of forms, with Javascript switching the images and information presented in each of the land use option sets.

[11] The full questionnaire and screen-shots of each treatment are available from the authors with selected VR images available from the web-site listed previously.

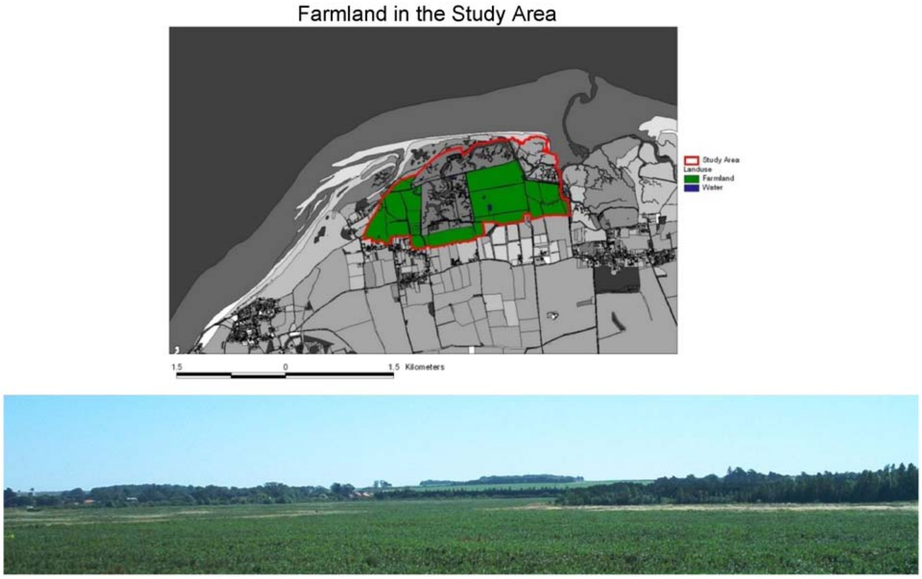

Fig. 2. Example of the introductory information presented to all participants in the experiment: location and photo of agricultural land within the survey area.

numeric form, as choices between the area of each land use type in the status quo and alternative options, both described through the numeric levels (in hectares) of each of the attributes. In the second treatment, denoted *VR*, the status quo versus alternative choice tasks were presented solely as the VR flythroughs described previously. Finally, in the third treatment, denoted *VR & NUMERIC*, the participants were presented with choices described both as VR flythroughs and in standard numeric form. In all treatments the level of the *Cost* attribute was always presented numerically. In all treatments, actual choices were only elicited after practice questions had been answered, allowing participants to familiarise themselves with their relevant information provision mode, the choice task and response format. Once all choice tasks had been completed the three treatments again became identical and a series of personal characteristic questions were posed so as to elicit potential explanatory covariates. On completion of a survey, data was automatically stored and sent to the survey facilitator.

2.4. Research questions and response modelling

The premise of our study is that the degree of evaluability of information provided in a CE may systematically affect subjects' responses. To test that we seek to estimate a model of preferences that can capture differences in responses between our low evaluability information sample (*NUMERIC*) and our high evaluability information samples (*VR* and *VR & NUMERIC*). The particular research questions we wish to address are as follows:

(i) Does our data demonstrate gain–loss asymmetry? In particular, is there evidence to support the contention that more highly evaluable information (*VR* treatments) reduces loss aversion relative to less evaluable information (*NUMERIC* treatment)?
(ii) Does increasingly evaluable information result in more precise expressions of preferences?

In specifying a model of preferences recall that the experiment presents respondents with a series of binary choice tasks in which they are asked to choose between the current composition of land use in the study area and an alternative composition of land use. As such, our data consists of observations on the responses of $i = 1, 2, \ldots, N$ individuals to $j = 1, 2, \ldots, J$ choice tasks. Each individual is allotted to one of these three treatment groups that differ in the means of presentation of information (*NUMERIC*, *VR*, *VR & NUMERIC*). We index treatments by $t = 1$, 2 or 3.

Our structural model follows the familiar random utility framework [45]. On each choice occasion individual i must choose between the status quo land use composition (Option 0) and some alternative land use composition (Option 1). We specify the utility from the status quo (Option 0) as

$$U_{ij0}^{t} = \boldsymbol{X}_0\boldsymbol{\beta}^t + \bar{\alpha}^t + \alpha_i + e_{ij0}^{t} \quad (1)$$

where $\boldsymbol{X}_0$ is a K-dimensional vector of attributes of the status quo; namely, the quantities of land in the study area dedicated to different land uses in the current state of the world and an associated price which is always zero. Since the area of land in the study location is fixed, the quantity of agricultural land is not included in the specification since this is totally determined by the quantities of *Reserve* and *Flooded* land (see footnote 4).

$\boldsymbol{\beta}^t$ is the *K*-dimensional vector of taste parameters. The parameters on quantities of *Reserve* and *Flooded* land should be interpreted as the marginal utility from an increase in land area dedicated to that usage at the expense of agricultural land.[12] The parameter on the cost attribute can be interpreted as the negative of the marginal utility of income. Of course, our core contention is that the evaluability of information provided to respondents affects expressed preferences. To that end, observe that the taste parameters are superscripted *t*, indicating that our model allows for the possibility that respondents in the different treatments will express different tastes for land use attributes.

$\bar{\alpha}^t$ is a parameter measuring the fixed level of utility derived from maintaining the status quo, independent of the attributes of the current state of the world. Notice that the status quo utility has the superscript *t*, indicating that our model allows for the possibility that this component of utility may also differ across treatments.

α_i is a parameter indicating a person-specific deviation from $\bar{\alpha}$.

e^t_{ij0} is a compound error term consisting of an econometric and structural component. The econometric component captures errors in specification of the utility function (for example, in individual variation in the taste parameters, $\boldsymbol{\beta}^t$). Since the characteristics of our samples do not differ systematically, we assume that the variance of this error component is constant across treatments. In the spirit of the psychometric tradition of comparative judgement [39,53], the structural component captures individual error in evaluating the magnitude of the benefit from a particular composition of land use when presented in a particular format. Since respondents may find different presentations easier to evaluate than others, we wish to allow for the possibility that the variance of this error component may differ with treatment. Again we use the superscript *t*, to indicate this fact.[13]

In contrast, the utility from the state of the world shown in the alternative option (Option 1) is

$$U^t_{ij1} = \boldsymbol{X}_{ij1}\beta^t + e^t_{ij1} \tag{2}$$

$\boldsymbol{X}_{ij1}$ is the *K*-dimensional vector of attributes of the alternative option; namely the quantities of different land uses in the alternative state of the world and an associated non-zero price. Again parameter identification is achieved by dropping the quantity of agricultural land.

e^t_{ij1} is a compound econometric and structural error term, where again we assume that the variance of the econometric component is invariant to treatment but the variance of the judgement error component may be dependent on the evaluability of the presentation of information.

The difference in the utility offered by the two options is then

$$u^t_{ij} = U^t_{ij1} - U^t_{ij0} = \boldsymbol{x}'_{ij}\boldsymbol{\beta}^t - \bar{a} - a_i + \varepsilon^t_{ij} \tag{3}$$

where $\boldsymbol{x}_{ij} = \boldsymbol{X}_{ij1} - \boldsymbol{X}_0$ and $\varepsilon^t_{ij0} = e^t_{ij1} - e^t_{ij0}$. Notice that with only weak assumptions, we can suppose that increasing variance in the utility error components (as would result from increasing judgement error associated with poorly evaluable information) translates into increasing variance in ε^t_{ij}.

As described in detail in the next section, Eq. (3) somewhat simplifies the specification. In order to test for gain–loss asymmetry, we include further treatment-specific parameters that identify how tastes for a land use differ when the alternative option offers a loss in that land use area (compared to the status quo) as opposed to a gain.

Given (3), the choice rule becomes

$$\text{If } u^t_{ij}\begin{cases} \leqslant 0 & \text{then choose Option 0 } (y_{ij} = 0) \\ > 0 & \text{then choose Option 1 } (y_{ij} = 1) \end{cases} \tag{4}$$

where y_{ij} is the dependent variable indicating whether individual *i* on choice occasion *j* selected the status quo (Option 0) or the alternative state of the world (Option 1).

If we assume that $\varepsilon^t_{ij} \sim \text{i.i.d.}N(0, \sigma^2_{\varepsilon^t})$ then the choice probabilities become

$$\begin{aligned} Pr[y_{ij} = 0] &= Pr\left[\frac{\varepsilon^t_{ij}}{\sigma_{\varepsilon^t}} \geqslant -\left(\frac{\boldsymbol{x}'_{ij}\boldsymbol{\beta}^t - \bar{\alpha}^t - \alpha_i}{\sigma_{\varepsilon^t}}\right)\right] = \Phi\left(-\left(\frac{\boldsymbol{x}'_{ij}\boldsymbol{\beta}^t - \bar{\alpha}^t - \alpha_i}{\sigma_{\varepsilon^t}}\right)\right) \\ Pr[y_{ij} = 1] &= Pr\left[\frac{\varepsilon^t_{ij}}{\sigma_{\varepsilon^t}} < -\left(\frac{\boldsymbol{x}'_{ij}\boldsymbol{\beta}^t - \bar{\alpha}^t - \alpha_i}{\sigma_{\varepsilon^t}}\right)\right] = 1 - \Phi\left(-\left(\frac{\boldsymbol{x}'_{ij}\boldsymbol{\beta}^t - \bar{\alpha}^t - \alpha_i}{\sigma_{\varepsilon^t}}\right)\right) = \Phi\left(\frac{\boldsymbol{x}'_{ij}\boldsymbol{\beta}^t - \bar{\alpha}^t - \alpha_i}{\sigma_{\varepsilon^t}}\right) \end{aligned} \tag{5}$$

where $\Phi(\cdot)$ is the cumulative distribution function of a standard normal and the equality in the final line follows from the symmetry of that function.

[12] Our model cannot determine whether positive (negative) taste parameters on the land use variables reflect positive (negative) preferences for *Reserve* or *Flooded* area or negative (positive) preferences for agricultural area. For ease of exposition, we choose to interpret parameters as reflecting preferences for *Reserve* or *Flooded* area. Of course, that particular assumption has no bearing on the key issue of whether gain/loss asymmetries in preferences (whether attributed to *Reserve*/*Flooded* area or to agricultural area) differ between the numeric and visual information treatments.

[13] Allowing for differences in the scale of the error term across treatments also addresses scale confounding as discussed by Swait and Louviere [51].

The last step in formulating the model is to complete the specification for the random effects, α_i. Following standard practice, we assume that these are distributed normally across the population; that is to say, $\alpha_i \sim$ i.i.d. $N(0,\sigma_\alpha^2)$. To normalise the model, let $\sigma_\alpha^2 = 1$. In that case, the likelihood contribution of individual i is

$$l_i = Pr[y_i] = \int_{-\infty}^{\infty} \phi(\alpha) \prod_{j=1}^{J} \Phi\left(q_{ij}\left(\frac{\boldsymbol{x}'_{ij}\boldsymbol{\beta}^t}{\sigma_{\varepsilon^t}} - \frac{\bar{\alpha}^t}{\sigma_{\varepsilon^t}} - \sqrt{\rho^t/(1-\rho^t)}\frac{\alpha}{\sigma_{\varepsilon^t}}\right)\right) d\alpha \tag{6}$$

where $\boldsymbol{y}_i$ is the J-vector formed by stacking the dependent variables, y_{ij}, for individual i; $q_{ij} = 2y_{ij}-1$, is a transformation of the dependent variable that simplifies presentation and calculation; $\rho^t = (\sigma_{\varepsilon^t}+1)^{-1}$, is the correlation between the responses of the same individual resulting from the person-specific random effect; $\phi(\cdot)$ is the probability density function of a standard normal.

The integral in (6) can be simply estimated using Gaussian quadrature. The log-likelihood function is then

$$\ln L = \sum_{i=1}^{N} \ln(l_i) \tag{7}$$

which can be maximised with respect to the parameters of the model using standard optimisation methods.

3. Results

The experiment was conducted within the Social Science for the Environment, Virtual Reality and Experimental Laboratories (SSEVREL) of the Zuckerman Institute for Connective Environmental Research (ZICER) at the University of East Anglia. Participants were contacted via an email invitation to all students at the university. Within the experiment a simple device calling for the participants' university username ensured that no individual could participate more than once in the study. In total 288 individuals participated in the experiment, each providing 16 choice responses.

We modelled those responses using the random effects probit model developed in the previous section. Table 1 reports parameter estimates from a specification of the model that captures the principal quantities under investigation. We found that more highly parameterised specifications, particularly those allowing for socioeconomic and demographic interactions, did not significantly alter our findings with regards to the central treatment variables. Accordingly these additional analyses are reported elsewhere [5] allowing us to concentrate upon a parsimonious analysis focussing on the main issues of interest to this study.

The specification in Table 1 takes the conventional presentation of information in CEs, that is the *NUMERIC* treatment, as the base case. Treatment effects are explored by interacting the variables of Eq. (3) with dummy variables identifying individuals facing the alternative treatments; one for the *VR* treatment and one for the *VR & NUMERIC* treatment.

Accordingly, preferences for the status quo, $\bar{\alpha}$ in Eq. (3), are captured through three variables; the "*Constant*" captures status quo preferences of those receiving the *NUMERIC* presentation, while "*Constant* × *VR*" and "*Constant* × *VR & NUMERIC*" capture deviations from that base case amongst those facing the alternative presentations. With regards to preferences for the status quo, we have no prior expectations of a presentation effect.

In contrast, our previous discussion suggests that improving the evaluability of the information provided in the CE may affect stated preferences for changes in land use. In particular, we hypothesise that the greater evaluability of VR representations of land use changes may act so as to ameliorate disproportionate aversion to losses when compared to affinity for gains. We explore this hypothesis with respect to preferences for the *Reserve* land use.[14] The base case, indicated "Reserve Area" in Table 1, measures preferences in the gains domain for individuals receiving the standard *NUMERIC* presentation. The "*Reserve Area* × *Loss*" parameter captures any deviation from those preferences in the loss domain (results confirm scope sensitivity within both the gain and loss domains). Four further interacted variables are included to capture deviations from these preferences amongst the alternative treatment groups.[15]

Finally, we investigate whether presentation influences the consistency of responses through the estimation of three treatment-specific variance parameters.

At the outset we tested for correlation in individuals' choices induced by the unobserved individual-specific preference parameter, α_i. A comparison of the random effects probit specification that allows for such correlation, with a standard probit specification that does not, led us to categorically reject the hypothesis that individuals' responses are independent ($LR\ stat = 432.2$, p-value <0.001).

From Table 1 we observe that there is no evidence for a treatment effect upon the utility associated with maintaining the status quo. Testing reveals that we cannot reject the hypothesis that all three $\bar{\alpha}$ parameters (see Eq. (3)) are identical and equal to zero ($LR\ stat = 2.266$, p-value $= 0.519$). As such, our data provides little support for the presence of a treatment-induced status quo bias. Signs on the *Cost* and *Flooded* parameters are, as expected, both negative. The *Flooded*

[14] In the interests of brevity, we only present results for models examining treatment effects for the *Reserve* land use. Models that also include treatment effects for *Flooded* land use have no material impact on the findings for *Reserve* land use and generally reinforce the key conclusions of our analysis.

[15] The *Loss* (*Gain*) term equals 1 if the change in *Reserve* area represents a reduction (increase) from the status quo and 0 otherwise.

Table 1
Parameter estimates from a random effects probit model with error variance differing across treatments.

Parameters	Coefficient estimate (std. err.)	*t*-stat	*p*-value
Constant	0.1834 (0.1610)	1.139	0.255
Constant × *VR*	−0.0050 (0.2129)	−0.023	0.981
Constant × *VR & NUMERIC*	−0.1189 (0.2205)	−0.539	0.590
Cost	−0.0306 (0.0027)	−11.439	<0.001
Flooded	−0.0012 (0.0005)	−2.214	0.027
Reserve Area	0.0069 (0.0034)	2.012	0.044
Reserve Area × *Gain* × *VR*	−0.0024 (0.0045)	−0.537	0.591
Reserve Area × *Gain* × *VR & NUMERIC*	−0.0025 (0.0044)	−0.565	0.572
Reserve Area × *Loss*	0.0217 (0.0056)	3.903	<0.001
Reserve Area × *Loss* × *VR*	−0.0135 (0.0035)	−3.867	<0.001
Reserve Area × *Loss* × *VR & NUMERIC*	−0.0124 (0.0035)	−3.550	<0.001
Error variance ($\sigma_\varepsilon{}^2$)			
NUMERIC	1.9388 (0.2415)	8.029	<0.001
VR	1.4604 (0.1509)	9.676	<0.001
VR & NUMERIC	1.1988 (0.1233)	9.726	<0.001
N	288		
ln *L*	−2220.370		

Table 2
Marginal welfare estimates for changes in reserve area.

Treatment	Marginal welfare (£/ha)	Standard error
Gains		
NUMERIC	0.2247	0.1129
VR	0.1463	0.0960
VR & NUMERIC	0.1429	0.0926
Losses		
NUMERIC	0.9345	0.1189
VR	0.4943	0.0762
VR & NUMERIC	0.5286	0.0783

area variable yields significant scope sensitivity (with the negative estimated parameter indicating that respondents see additional *Flooded* areas as constituting a loss of utility).[16]

Our central results are derived from the various parameters estimated on the *Reserve* area variables. These can be used to construct marginal values for the different treatments in the gain and loss frames.[17] Table 2 presents resultant marginal welfare estimates with associated standard errors estimated using the delta method. Given the central thesis of this study it seems only appropriate to illustrate these principal results visually, as per Fig. 3. This plots out marginal values as linear value functions and graphically demonstrates the central results of our analysis.

Considering Table 2 and Fig. 3, respondents in the *VR* and *VR & NUMERIC* presentation treatments value changes in *Reserve* area almost identically. In the loss frame the difference between the marginal value for these two treatments is around £0.03 whilst in the gains frame the difference is less than half a penny. Table 3 provides formal statistical tests of the equivalence of these marginal value measures. We find that we cannot reject the hypothesis that individuals in these

[16] While the disutility associated with additional *Flooded* areas is hardly surprising, nevertheless from an ecological perspective such areas are of high biodiversity habitat value. This seems to demonstrate a commonly asserted problem of preference-based decision systems; most individuals do not like muddy saltwater flooded areas and are either unaware or do not care about the creatures that live there. The fact that such creatures frequently form a vital link in biodiversity support systems is not one readily appreciated by the typical individual.

[17] To do this one simply sums the parameters specific to a particular treatment in a particular frame and then divides through by the negative of the coefficient on cost. For example, estimated marginal value for the *VR* treatment group in the gains frame is $\hat{W}_{VR}^{Gain} = 0.0069 - 0.0024/0.0306 =$ £0.15. Likewise, the estimated marginal value for the *VR* treatment group in the losses frame is $\hat{W}_{VR}^{Gain} = 0.0069 + 0.0217 + 0.0135/0.0306 =$ £0.49.

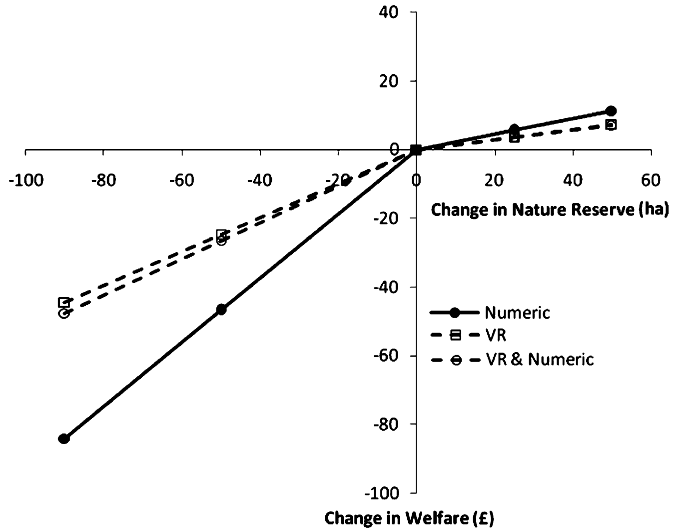

Fig. 3. Value functions for changes in area of nature reserve by treatment group.

Table 3
Tests of equality of marginal welfare values for reserve area across treatments.

Treatments	Welfare difference (std. error)	*z*-score	*p*-value
Gains			
VR vs. *VR & NUMERIC*	−0.0033 (0.2586)	−0.013	0.990
NUMERIC vs. *VR*	−0.0784 (0.1462)	−0.537	0.591
NUMERIC vs. *VR & NUMERIC*	−0.0818 (0.1448)	−0.564	0.572
Losses			
VR vs. *VR & NUMERIC*	0.0343 (0.2083)	0.165	0.869
NUMERIC vs. *VR*	−0.4402 (0.1213)	−3.628	0.000
NUMERIC vs. *VR & NUMERIC*	−0.4059 (0.1210)	−3.355	0.000
Gain/loss asymmetry			
NUMERIC	0.7098 (0.1939)	3.660	0.000
VR	0.3480 (0.2355)	1.478	0.139
VR & NUMERIC	0.3857 (0.2361)	1.634	0.102
Differences in gain/loss asymmetry			
VR vs. *VR & NUMERIC*	−0.0377 (0.2377)	−0.159	0.874
NUMERIC vs. *VR*	0.3618 (0.1218)	2.970	0.003
NUMERIC vs. *VR & NUMERIC*	0.3241 (0.1207)	2.684	0.007

two treatments groups value changes in reserve area identically; both in the gains frame (p-value = 0.990) and in the loss frame (p-value = 0.869).

In contrast to this, the *NUMERIC* only treatment group have larger marginal *WTP* for changes in *Reserve Area*, with that difference being most apparent in the loss frame. It appears that respondents consider changes in the area of *Reserve* more significant when the information is conveyed to them in numeric form alone than when they are additionally or solely presented with a *VR* presentation. Again, formal statistical tests of these differences in valuation are presented in Table 3. We find that we cannot reject the hypothesis of equal valuation in the gains frame (the comparison of the *NUMERIC* only group with the *VR* group returns a p-value of 0.591, while that with the *VR & NUMERIC* group returns a p-value of 0.572). On the other hand, in the loss frame we find that the *NUMERIC* only group give very significantly higher valuations than either other group (comparison of the *NUMERIC* only group with both the *VR* group and the *VR & NUMERIC* group returns a p-value of <0.001).

Our data suggest that, compared to the standard *NUMERIC* presentation, providing *VR* presentations of changes in *Reserve* area has the effect of significantly reducing respondents' marginal valuation of losses. Following the evaluability literature discussed previously, it appears that the *VR* presentation provides respondents with the ability to more thoroughly evaluate the scale of those changes; what might appear like a major change in *Reserve* area when presented as a figure in hectares may not seem so substantial when viewed via virtual reality. It seems plausible to suggest that such improved evaluability results in less reliance upon response heuristics such as loss aversion. This in turn implies that there will be a less distorted reflection of underlying economic-theoretic preferences within such responses.

Considering the issue of gain/loss asymmetry, observe from Table 2 and Fig. 3 that in all three treatments, respondents value losses more highly than gains; a pattern of loss-aversion regularly recorded in the literature [27]. However, as shown in Table 3, this gain/loss asymmetry is very significantly greater for the *NUMERIC* only presentation (a difference in marginal values of losses relative to gains of £0.71) than for the *VR* treatment group (a difference of £0.35) or the *VR & NUMERIC* treatment group (a difference of £0.39). Moreover, we find that we can reject the hypothesis of equality of marginal valuations in the gains and losses frames for the *NUMERIC* group at the 1% level of confidence. In contrast for the *VR* group and the *VR & NUMERIC* group the difference between marginal valuations of gains and losses is not significant. The final three rows of Table 3 show that the gain/loss asymmetry exhibited by the *NUMERIC* group is significantly larger than that shown by either of the other treatment groups (in both cases p-values are <0.01), while the asymmetry shown by the *VR* group and the *VR & NUMERIC* group are statistically indistinguishable.

Clearly, gain/loss asymmetry is a feature of this data but the magnitude of that asymmetry is considerably ameliorated amongst groups receiving a *VR* presentation of the land use change information. Indeed, in our data we cannot reject the hypothesis that there is no gain/loss asymmetry in those groups. Again, we might conjecture that this pattern is symptomatic of respondents expressing greater levels of loss-aversion in the situation in which they have difficulty evaluating the scale of the loss they might suffer.

A final issue is to consider whether there is evidence to support the notion that, in improving evaluability, *VR* treatments also reduce variability in responses. Recall that the random element in our random utility model is motivated as capturing both econometric misspecification, the variance of which we assume remains constant across treatment samples, and respondent imprecision, the variance of which we assume declines with increasing evaluability. To that end, we compare the model in Table 1 to one in which the error variances are constrained to be equal across treatments and find that we can reject the hypothesis of equality of error variance ($LR\ stat = 9.97$, p-value $= 0.007$). Observe from Table 1 that the error variance is greatest for those in the *NUMERIC* only treatment group (1.938), somewhat less in the *VR* treatment group (1.460) and least in the *VR & NUMERIC* treatment group (1.199). It appears that the increased evaluability of the information provided by the *VR* presentations does indeed reduce the variability in respondents' expressed preferences succinct.

4. Discussion and conclusions

The developing literature on evaluability shows that when individuals make decisions on the basis of information they insufficiently comprehend they are likely to rely upon various heuristics and rules of thumb to make those decisions. These cues are often taken from the framing of decisions and can therefore be manipulated by respecification of such frames. Within the context of valuation surveys this results in stated preferences which fail to conform to economic-theoretic requirements, instead exhibiting a range of recognised anomalies of which the asymmetry of gains and losses is one of the best documented. Such preferences cannot be used for economic decision-making purposes. The same evaluability literature, however, suggests that the mode of information provision can be the key to ensuring its comprehension. Sole reliance upon numeric information has been shown to be inferior to the inclusion of visual representations of data in conveying the accurate meaning of information.

The present study investigates the issue of evaluability by contrasting conventional numeric modes of information provision with visual and combined visual and numeric approaches. Recent advances in *VR* technology are employed to generate visual representations which are either combined or contrasted with numeric treatments. Our case study allowed for both gains and losses in a valued land use, a situation which under conventional, numeric only, treatments typically generates major asymmetries between associated value measures. Our conventional numeric treatment does indeed generate very marked gain/loss asymmetry, with the loss-aversion heuristic influential in determining stated preferences. However this asymmetry was markedly lower amongst groups presented with visual, VR-based representations of the same choices. In particular, loss dimension values were significantly lower in groups viewing VR images compared to values elicited from those respondents who were only presented with conventional numeric information. Importantly, there is also evidence to suggest that the use of visual information reduces the magnitude of judgement errors as demonstrated by a reduction in error variance amongst groups presented with the *VR* treatments.

We believe that these findings have the important yet straightforward message that researchers need to be aware of the challenge of evaluability when using numeric representations of attribute levels, especially where respondents find the units used cognitively challenging. The evaluability literature suggests that this criticism might well be applied to a large number (possibly the majority) of CE studies conducted upon non-market environmental goods to date. However, the same literature and our own empirical findings also offer a hopeful message. The new, VR-based approach to *CE* valuations which we develop through this paper offers a method of directly addressing the evaluability problems of certain numeric information (particularly regarding changes in the provision of primarily visual environmental goods such as land use change). By linking VR technology through to GIS databases, realistic, accurate and evaluable representations of real-world environments can be generated. Furthermore, once generated (and that generation process is becoming rapidly easier with the ongoing development of VR software), such virtual environments are readily employed in either the laboratory or field. We believe that such innovations may allow a leap forward in non-market valuation techniques, permitting researchers to convey realistic policy change scenarios in a manner which, as we demonstrate in the present study, directly reduces reliance upon response heuristics and consequent anomalies and thereby allows underlying preferences to be more effectively measured. In so doing we may well prove by weight of evidence that the apparently ubiquitous problem of gain/loss asymmetry can, at least to some significant degree, be explained and addressed through an appeal to evaluability.

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