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A NEW APPROACH TO CAPTURING THE SPATIAL DIMENSIONS OF VALUE WITHIN CHOICE EXPERIMENTS

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0 Abstract:

Both theoretical expectations and empirical regularities indicate that individuals' preferences for spatially located goods vary with distance to those goods. Most obvious is the well documented 'distance decay' effect whereby willingness to pay for certain use value goods declines with increasing distance. Understanding how value of environmental goods and services is influenced by their location relative to respondents can allow designing optimal spatial distribution of conservation interventions across landscapes. However, capturing these spatial relationships within the two-dimensional confines of most stated preference studies has proved a challenge. We propose and implement a novel approach to bringing space into choice experiments (CE). Using an investigation of preferences concerning land use change in Great Britain (GB), CE scenarios are presented on individually generated maps, tailored to each respondent's home location. Each choice situation is underpinned by spatial experimental designs relevant to the individual's spatial context and a matrix of British current land uses defined at a 2km scale resolution. To the best of our knowledge, this represents the first case of a CE that integrates space into both the design and presentation of options. We test the effect of our map format for presenting spatial attributes against a commonly applied tabular approach, finding that the former yields both significantly different and more robust preference estimates. At a time of growing public use of mapping software and applications (e.g. Google/Apple maps) this approach appears to significantly enhance respondents' understanding of key spatial dimensions of goods while also providing analysts with an enhanced basis for the spatial transferal of valuation results and their incorporation within decision making support systems.

JEL Codes and Keywords:
Q51 Valuation of Environmental Effects; Q57 Ecological Economics: Ecosystem Services; Biodiversity Conservation; Bioeconomics; Industrial Ecology; Q180 Agricultural Policy; Food Policy; Q260 Recreational Aspects of Natural Resources; Q15 Land Ownership and Tenure; Land Reform; Land Use; Irrigation; Agriculture and Environment.

1 Introduction

Increasingly choice experiments (CE; Louviere and Hensher 1982, Louviere and Woodworth 1983) have been used to inform decisions makers on preferences for hypothetical future environmental changes (e.g. Johnston et al. forthcoming). At the same time researchers have stressed the importance of ensuring the validity and reliability of elicited welfare estimates (Johnston et al. forthcoming, Desvousges et al 2016). Substantial progress has been made to develop informative and valid CE for environmental decision making. For example, the effect of attributes, levels, number of choice cards and order has been extensively tested (De Shazo and Fermo 2002, Day and Pinto Prades 2010, Day et al. 2012, Meyerhoff et al 2015), as well as the effect of information (Czajkowski et al. 2016b), sensitivity to scope (Czajkowski and Hanley 2009), design and status quo choices (Boxal et al. 2009, Oehlmann et al. 2017) and attribute non-attendance (Hussen Alemu et al. 2013).

Another factor that has been shown to be fundamentally important in determining values of environmental related goods and services (not solely) in CE is space. This role is rather complex. The physical characteristics of ecosystems vary across space, this affects both their physical capacity to produce ecosystem services, and the potential for these services to benefit people and generate value. Ecosystem related goods and services from which humans benefit vary across space (at least) in terms of biophysical processes, beneficiaries and benefits, as well as in terms of costs of ecosystem service provision (Fisher et al. 2011). For example, water purification or flood protection services materialise solely upstream relative to beneficiaries, while economic benefits of pollination occur only in areas where food is harvested. Similarly, for some of the values the proximity to human settlements affects the realisation of these values - e.g. green space located close to residential areas has the potential to generate large recreational benefits, whereas an equivalent green space located in remote and/or inaccessible areas provides limited recreational benefits. To add further complexity to these value-space relationships, it has also been shown that values differ for different environmental goods, habitats and locations (e.g. Interis and Petrolia, 2016) and that respondents might have varying degree of "distance sensitivity" to different types of goods and sites (e.g. Schaafsma et al. 2013). Environmental policies are likely to simultaneously generate changes in ecosystem services and benefits at specific location and time (Rodriguez et al. 2006, Fisher et al. 2009, Fisher and Turner 2008). Understanding of spatial trade-offs between competing land uses, particularly between conservation and agriculture or urban development, is crucial for targeting policy interventions with greatest welfare returns for the society (e.g. Bateman et al. 2013). Clearly, the spatial configuration and characteristics of ecosystems and their beneficiaries matter in ecosystem service assessments and their valuation (e.g. Bateman et al. 2011, Fisher et al. 2011) which is reflected in the valuation fields' increased interest in it.

This paper aims to contribute to the research relating to space-value relationships by presenting a novel approach for spatially-relevant choice experiments The methodology aims to improve our understanding of how space and its presentation in choice experiments influence preferences for land use related environmental interventions and is applied on a case study of valuing preferences for such changes in Great Britain. It incorporates space in different stages of the choice experiment - in the experimental design, in survey instrument design and in the way choice set is presented, and analysis. This approach builds on the previous research in choice experiments (and stated preference broadly) and aims to contribute to its effort to increase the spatial validity of valuation research.

1.1 Space in choice experiments

The incorporation of space in the modelling of CE is growing fast (e.g. Brouwer et al. 2010, Campbell et al. 2008, 2009 Czajkowski et al. 2016a, Johnston et al. 2002, 2016, Johnston and Ramachandran 2014, Schaafsma et al. 2012, 2013, Schaafsma and Brouwer 2013) and for a decade the space dimension was mainly captured in the analysis of the data. Recently, the treatment the space has expanded to considering its role in representing choice situations (e.g. Johnston et al. 2016).

The initial interest in spatial aspects of preferences for environmental changes in stated preference valuation studies was predominantly motivated by the definition of relevant markets for aggregation of estimated values (e.g. Sutherland and Walsh 1985, Pate and Loomis 1997). Distance is known to influence values in the revealed preference literature (e.g. Bocksteal and McConnell 2007). In the context of CEs, initial studies included distance to the valued site, good and/or service in the attribute description (e.g. Adamowicz et al. 1994). Often termed distance decay function (Loomis 2000) - the phenomenon of decreasing magnitude of elicited values with increasing distance of a beneficiary to a valued site and/or good/service - has been documented by an expanding body of literature (e.g. Bateman et al. 2006, Schaafsma et al. 2012, 2013, Liekens et al. 2013). Distance decay has been shown to vary across users and non-users (e.g. Bateman et al. 2006, Schaafsma et al. 2013) and is influenced by the availability and proximity of substitutes (e.g. Schaafsma et al. 2012, De Valck et al. 2017), with significant implications for value aggregation. Beyond physical space, people show heterogeneous preferences across political boundaries, for example, exhibiting nationalistic premiums for environmental goods and services located in respondent's country of residence (Dallimer et al. 2014).

The use of maps in CE representation is intended to provide better means for portraying the spatial context of choice situations and has been shown to capture some of these effects on preferences. Spatial information has also been shown to impact on both spatial and non-spatial policy attributes (Johnston et al. 2002). This information is generally portrayed in terms of generic maps that are identical for all CE respondents (Johnston et al. 2016). Individualized spatial information, such as individually tailored maps of the areas of change, influence the preference values (e.g. Johnston et al. 2016). Johnston et al. (2016) measure the impact of individualized maps in contrast to generic maps in CE representation, however other pending questions on space and its incorporation remain unanswered.

1.2 Spatially tailored choice experiment

This paper incorporates a number of spatial aspects in the survey design and presentation of choice experiments. It builds on three sources of information - respondent's home location, actual spatial availability of sites for environmental change in case study region and two location attributes (respondent's distance from the site and country where the site is). The study employs a novel use of experimental design techniques to generate spatially explicit choice sets and the representation of these choice sets is uniquely generated on individualized maps through a functionality that has been developed with professional programmers. Complementary to Johnston et al (2016)'s work this study measures the impact of presenting the choice alternatives on individualized maps on welfare estimates compared to the traditionally used table format. So while Johnston et al (2016) compare a generic map vs individualized maps, in this study we compare individualized maps vs tabular attribute CE. To our knowledge, this is the first study that incorporates spatial information in both design and presentation phases of choice experiments in an attempt to improve the reliability of evidence for policy making and advice. We provide evidence that the methodology presented in this paper is likely to result in better value estimates for value assessments that are spatially relevant and hence can improve the current CE research.

We apply this methodology on eliciting preferences for conservation interventions in high intensity agricultural landscapes in Great Britain, interventions that are broadly relevant to agri-environmental policies in the UK and EU. Land use change of such type raises many complex spatial-value relationships. Conservation sites often generate a bundle of ecosystem services (e.g. biodiversity protection, water purification and regulation, recreation or carbon storage), while agricultural land is predominantly associated with food production that is essential for each country's food security, but also with biodiversity protection or carbon sequestration when managed extensively. Further, conservation sites usually embody non-use values through safeguarding biodiversity, but also in many cases offer opportunities for recreation that embody a strong use value component for people. The opportunity costs of conservation in agricultural landscapes and "conservation returns" are in many cases highly spatially heterogeneous due to variation of land productivity and species occurrence (e.g. Bateman et al. 2016). Valuing interventions in high intensity agricultural landscape hence represent a useful context to test the performance of the presented approach.

The paper has the following structure. The second section will provide an overview of the CE survey instrument design and explain the novel functionality developed for this research. The third section provides a description of the empirical approach to examine the effects of the novel presentation of choice sets and means for deriving the value transfer function for conservation interventions in agricultural landscapes of GB. The fourth section provides results of mixed logit models in preference and WTP space. The fifth section discussed implications of the results for the CE research field and discusses how the welfare values derived for the case study region could be used to identify optimal locations for land use interventions. Finally the paper concludes.

2 Methodology: Survey instrument development

This survey focuses on valuing conservation changes to high intensity agriculture in Great Britain that has positive impacts on biodiversity. In the United Kingdom, agricultural landscapes cover around 17.1 million hectares or 70% of its land (DEFRA et al. 2016) and its intensification over the past four decades[1] has been the major driver of biodiversity loss in the UK (Hayhow et al. 2016, Burns et al. 2016). The interventions valued in the survey are broadly relevant to agri-environmental schemes which were introduced in the EU and UK under reforms of the EU Common Agricultural Policy to address the increased concern about the negative environmental impacts of agriculture.

The survey provides means for assessing the preferences for such interventions by exposing respondents to 12 choices between three locations for intervention sites with varying characteristics and associated costs, with the opt-out option to leave the status of intensive agriculture practice unchanged. The web based survey instrument was piloted and refined over the course of 7 months – in terms of the survey wording, presentation and experimental design. Four pilot stages of the survey were implemented before reaching the final iteration that was used to collect the data presented in this paper (i.e. excluding the responses to previous iterations of the survey). The initial stage of piloting involved in-person implementation of the survey in order to ensure comprehension of the survey and avoid any missing information for the respondents in the described scenarios. In its final iteration, the survey is presented in 10 treatment formats (see Appendix) which provides the means for testing the impact of the novel choice set presentation, ordering of questions, and the stability of preferences. This paper focuses on the impact of choice set presentation.

2.1 The Spatial Choice Experiment

2.1.1 Valuation Scenario

The valuation scenario concentrated on two types of land use change from the status quo of intensive agricultural landscape. In a randomised manner, half of the choice questions for each respondent concerned on interventions aiming to transform the agricultural landscape into a less intensive one, while the other half described measures to plant new woodlands in the area. Each scenario was described and compared against the status quo (i.e. intensive agriculture) in terms of: amount of food produced; livestock density; levels of inputs used; effects on water quality in rivers; and impacts on wildlife the area (see Figure 1). Each land use type was accompanied by figures selected to represent the typical view of each. In

[1] Through dramatic changes in farming practices including increased use of chemicals the UK agriculture almost doubled milk and wheat yields since the 1970s (Hayhow et al. 2016).

order to ensure the comprehension of the survey scenarios a simple quiz testing the understanding of the main dimensions of change was presented after each scenario.[2]

Figure 1 – Example valuation scenario (AGRI)

One way to reduce the negative environmental impact of high intensity farming is to change some of these areas into **low intensity farming** (see pictures on the right hand column - scroll over the pictures to enlarge them).

In these areas this would lead to the effects described in the table below. These changes take a number of years to have their full effects.

	High intensity farming	Change to low intensity farming
Amount of food grown	High levels of food produced per acre	Lower levels of food produced per acre
Number of farm animals	High numbers of animals per acre	Lower numbers of animals per acre
Levels of inputs used	High levels of fertilisers, pesticides and machinery used	Lower levels of fertilisers, pesticides and machinery used
Effects on water quality in rivers	Likely to pollute nearby rivers	Unlikely to pollute nearby rivers
Effects on wildlife	Main cause of declines in UK wildlife, e.g. significant loss of certain bird species over the past 40 years	Increase in wildlife, e.g. greater numbers and varieties of birds

2.1.2 Attributes selection

A combination of piloting, literature review, current policy context and consultation with experts[3] was employed as inputs and motivation for the attribute selection procedure. The process was intended to provide three categories of attributes capturing the relevant characteristics of the land use interventions valued in the survey: 1) locational attributes 2) site characteristic attributes and 3) cost attribute (see Table 1; see Appendix for how the attributes were presented).

Distance and country were selected as relevant **location attributes** which were used to reflect the spatial dimension of value in the choice experiment. Respondent-to-site ***distance*** captures the heterogeneous influence of space on both use and non-use values (e.g. Bateman et al. 2006). The ***country*** attribute - i.e. whether the site is in the same country of Great Britain as respondent's home location - captures the impact of political boundary of space on preferences for change (e.g. Dallimer et al. 2014).

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[2] Respondents were allowed to continue with the survey only after the correct answer was selected aiming to ensure the comprehension of the main dimension of change presented in the survey. An option to revise previously given information was available for answering the quiz.

[3] Ecology/ornithology – Gavin Siriwardena, Environmental Economics and stated preference valuation – prof. Ian Bateman, Choice modelling and stated preference valuation – Dr. Silvia Ferrini, Prof. Michael Burton.

Table 1 – attribute levels

Locational attributes	
country	site located in the same country as respondent
	site located in other country than respondent
distance	site located less than 60 miles from respondent's home location
	site located more than 60 miles from respondent's home location
Site characteristic attributes	
access	site will be accessible for recreation
	site is closed to the public
size	small (7 ha)
	medium (100 ha)
	large (400 ha)
birds	Little or no increase in the number of birds and wildlife already present in the area
	Some increase in the number of birds and wildlife already present in the area
	Substantial increase in the number of birds and wildlife already present in the area
	Substantial increase in the number of birds and wildlife already present; Some increase in the number of species in the area
	Substantial increase in the number of birds and wildlife already present; Substantial increase in the number of species in the area
Cost attribute	
price	£15 increase in water bills per annum
	£30 increase in water bills per annum
	£70 increase in water bills per annum
	£100 increase in water bills per annum
	£150 increase in water bills per annum
	£200 increase in water bills per annum

Three **site characteristics attributes** – birds, size and access – provide the main descriptors of scenario change. First, the ***birds*** attribute provides a biodiversity dimension of land use change portrayed in the survey, relevant to both land use chance scenarios. This was motivated by a national, EU and global use of bird indicators to report on the progress of meeting associated biodiversity targets and use of birds for capturing broader changes in wildlife. Following a consultation with expert ecologists, the birds attribute was chosen such that it embodied two dimension of bird population change likely to result from different levels of conservation interventions. The intensity of conservation interventions are likely to impact on both species abundance (i.e. number of birds of existing species in the area) and species richness (i.e. number of birds species in the area). Both dimensions were reflected in the attribute presentation, together with links to other wildlife (see Table 1). The two dimensions of change were visually aided by the use of pictograms reflecting both species abundance and richness. Second, three ***size*** attribute levels reflected the need to account for the scope sensitivity in valuation exercises (see e.g. Johnston et al. 2017, Czajkowski and Hanley 2009, Carson), as well as aiming to use the estimated values for value transfer function to evaluate welfare impacts of different broad scale policy interventions in the GB. Third, ***access*** dummy attribute allowed capturing the use and non-use dimension of values elicited. While access by itself could be linked to values related to recreation value potential of the sites, the non-accessibility allowed analysing the non-use value of biodiversity and portrayed changes.

A ***cost*** attribute was included as a standard practice for deriving marginal WTP values for each attribute. The payment vehicle for this survey was chosen to be annual water bills. This was motivated by the literature review, the fact that all residents in the UK are faced by the water bills and that water bills are already used as a vehicle for paying for environmental improvements under the Ofwat 2019 Price Review process[4].

2.1.3 Experimental design

We employed Ngene software[5] for generating experimental designs for this survey. The Bayesian prior approach using the D efficient design was employed, reflecting the aim to test the impact of the novel presentation of the choice set while also aiming to derive efficient WTP values. The design was updated in a sequential manner (Scarpa et al., 2007). In the initial version of the experimental design the D priors were based on attributes' expected signs (Sandor and Wedel 2001). In the subsequent rounds, priors were updated by estimated model results at each stage of piloting. In total the priors were updated four times.

An innovative use of model averaging approach to experimental design (Rose et al. 2009) was used to incorporate spatial dimension of land use change in the design. We included both location attributes (country and distance) in the experimental design in the following way. The distance attribute was included as continuous variable, but having only two levels in the design – 1) less than 60miles; and 2) more than 60, with average values for each category estimated from previous versions of the survey. The country attribute was treated as a dummy with two levels – same country or other country to the one that the valued site is located in. This results in four possible combinations of country and distance attributes. However, only respondents located within 60 miles of the two borders in GB (England&Wales and England&Scotland) were physically possible to be faced by all four combinations. In other areas of GB, the combination of "other country" and "less than 60 miles" was an infeasible choice. All four possible combinations were considered in deriving the CE design. Two pivot designs were created. The first design was given to respondents living within the border areas for whom all possible combinations of country and distance attributes was allowed. The other design was assigned to respondents with restricted options, i.e. without the "other country" & "less than 60 miles" combination. The two designs were optimised to minimise the Bayesian D-error through model averaging approach in Ngene.

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[4] In order to increase the credibility of the payment vehicle an explicit link to water quality was made in the description of the portrayed interventions.

[5] See http://www.choice-metrics.com/features.html for further information

2.1.4 Spatial choice set generation functionality

The crucial functionality and novel approach of this valuation survey is how each choice set was generated in real-time and how it was presented in a spatially explicit format. This functionality was underpinned by input of respondent's home location, experimental design and a large 2km data set of (over 55 thousand) cells comprising the GB land coverage, each with the most recent land use characteristics. This dataset, for example previously used in Bateman et al. (2013), allowed us to describe land use changes which really reflect current land uses in GB. Through analysis of this dataset using the GIS, the subset of intensive agriculture cells were selected and randomly allocated for generating the choice experiment cards.

Each choice set was generated in following this functionality: first, the respondent's home location determined whether she received choice sets from the restricted or non-restricted design, respondents within 60 miles of a country border received sets from the unrestricted design (see Experimental design above).Second, the country attribute restricts the available cells for land use scenarios to those either within or outside respondent's country. Third, the cells are further restricted by empirical information on the real world location of high intensity agriculture. Fourth, a cell is randomly chosen from the remaining subset of cells. The actual distance from this cell to respondent's home is calculated. When this distance satisfies the experimental design classes (more or less than 60) the first option of choice card is created and distance displayed. Contrary to this, if the randomly allocated cell fails to satisfy the distance level given by the design the fourth step is repeated until satisfactory result is reached. The same procedure is repeated for all three land use options displayed in the choice cards (Fig. 2). This process was occurring real time when taking the survey and the requirement of this happening in fraction of second(s) posed a number of programming difficulties which were overcome with a help of professional programmers. The design hence incorporates distance in a two-step approach. In the first step, the spatial pivot design aims to cluster respondents according to their location. In the second, alternative intervention sites for each choice set were spatially randomly allocated within each of the two given distance attribute categories[6].

The choice cards were visually represented on a map together with respondent's home location (see Figure 2 below). Attribute levels (all but country) of choice experiment options were displayed in tables next to the map. To help respondents to more easily associate the location on a map with each attribute table, letters and colour coding were used[7] to strengthen this association. Further, to keep respondents reminded of the current

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[6] This effectively ensured a sufficient variability in the distance variables across the alternatives.

[7] Colours were chosen in a manner to avoid any common colour-blindness problems. Thanks to Dr. Amy Binner for pointing this out in the design stage of this survey.

intervention scenario (and to distinguish the choice sets across the two scenarios of change), a picture previously used in the scenario description was also displayed alongside each table (with status quo - no change option - displaying the picture used to describe high intensity agriculture). An information icon was included to provide respondents the opportunity to consult previously displayed information about each scenario or table of attribute levels to assist their choices. Each map displayed the names of each country in Great Britain, the border between the countries and the capital city of each of these. [8]

Through the portrayal of the location attributes and respondent's home location on each choice set it was expected to provide better understanding of the spatial context for respondents. We believe that this is likely to enhance understanding of the spatial choices for the respondents by presenting it in a familiar and accessible format given the current widespread use of mapping software online and on mobile phones for navigation globally and in the UK. This presentation contrasts with previous research in three ways. First, still in a significant number of the valuation studies the spatial context is presented in an abstract way, in a tabular format (i.e. distance is treated only as an abstract distance, with no direction, nor visual representation; e.g. Adamowicz et al. 1994, Luisetti et al. 2011, Liekens et al. 2013). Second, in cases where maps are used in CE studies the maps are rarely, if at all, individualised by making each respondent's location explicit (e.g. Johnston et al. 2016). Third, only rarely is the choice set generated in real-time and reflects the current situation in choice study context. To our knowledge, this functionality was employed for the first time in CE research and represents the incorporation of space in the valuation exercise in the most advanced manner to date.

To assess the effect of this novel form of choice set presentation on the choices made by respondents (and by extension the estimates of willingness to pay), a survey with an identical experimental design and functionality was presented to a subsample of respondents. However, in this version the map presentation (NoMap treatment) was replaced by the standard tabular format (as per Figure 2 below, however this time with the name of the country in which the site is located in the table). This 'control' group allowed us to isolate and test the effects of this novel choice set presentation. Further, the survey aimed to evaluate the effects of map presentation within respondents. At the end of the choice questions, the NoMap subsample were faced with two additional choice questions, both of which they had already answered over the course of the survey, however this time the choice sets were presented in map format. This subsample were also asked some additional questions regarding their opinions on the Map vs NoMap presentation.

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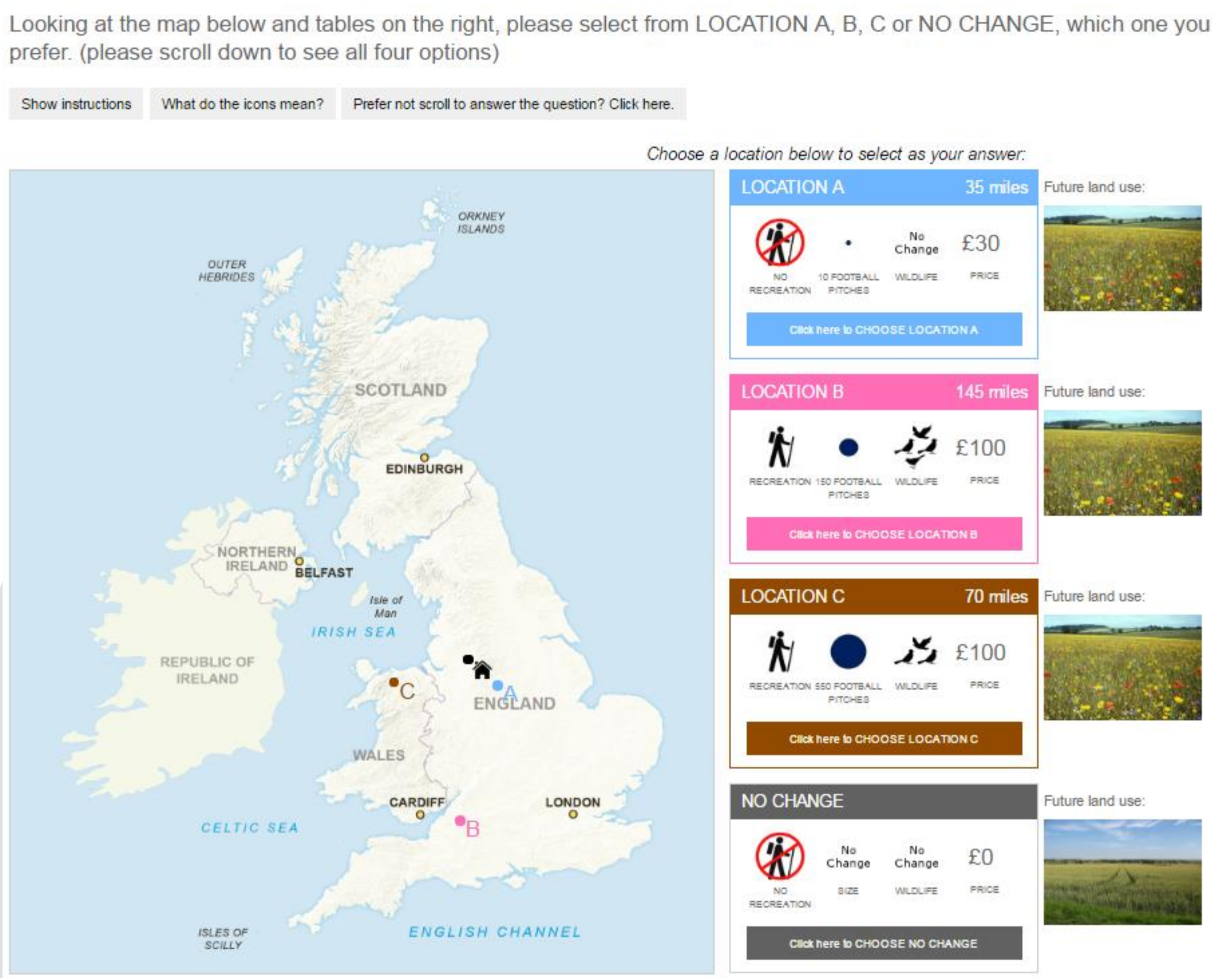
[8] While we would see benefit from additional spatial information (e.g. other major cities or satellite type of map) through more detailed spatial information we believed that in the current format this would clutter the choice set image and hence was not included.

Figure 2 – Choice set example



2.2 Data

The final dataset collected for the survey comprised of a representative sample of the population of the Great Britain. The sample respondents were facilitated by a professional panel provider that ensured that the sample was representative. In order to collect sufficient sample responses to estimate the country parameter a fixed quota for responses from England, Scotland and Wales was set at 68%, 16%, 16%, respectively. The responses to the final version of the survey were collected online, over the course of 2 months (August – September 2016).

Table 2 below reports some of the characteristics of the final sample used for the analysis, alongside a number of follow up questions and questions related to the opinion on the survey.

The full sample was cleared from identified protest voters and respondents which were identified as inattentive[9] to the survey to be able to provide valid responses for the CE exercise.

Table 2 Descriptive statistics of the sample

Variable	**Mean**	**Std. Dev.**	**Variable description**
Socio-economic variables			
Gender	0.5	0.5	0=male; 1=female
Age	49.6	16.4	Age categories in 10 years
Income (£/m)	3015.8	1837.8	Total monthly household income before tax
Follow up questions			
Policy impact	5.6	1.9	How likely is this survey to influence policy 1=least 10=most likely
Nature visits	2.5	0.9	How often respondents make trips to outdoor for recreation. 1=never -> 5=every day
Survey-related variables			
# SQ choice	1.9	2.7	Number of times respondent chose Status Quo
Quiz 1	1.6	2.1	Number of attempts to answer the first quiz
Quiz 2	1.5	1.9	Number of attempts to answer the second quiz
Survey time	22.4	103.1	How many minutes it took to answer the survey
Difficult choices	2.4	1.1	How easy or difficult you found making the choices. 1=very easy -> 5=very difficult

[9] Inattentiveness was determined by identifying respondents who spent an infeasible short time answering the survey, a feasible minimum time limit was assessed through testing with focus groups.

3 Empirical approach

In this paper we will report results from three different models and this section provides overview of the empirical approach employed. First, we set out a theoretical model which allows to generate testable hypotheses. Second, we outline the modelling strategies for estimating mixed logit models in preference and WTP space. Thirdly we discuss the empirical strategy to assess the impact of Map presentation on preferences in the presented spatial CE data.

3.1 Random utility maximisation and spatial attributes

The discrete choice models are grounded in Random Utility Maximisation theory (McFadden, 1973). It assumes that in choices between particular number of alternatives a respondent chooses an alternative with the highest level of utility (U) which is composed of deterministic part of utility observed by the researcher (V), which is a function of an individual set of preference parameters (β) for observable attributes (x) of the alternative, and a random part of the utility (ε).

$$U = V(x, \beta) + \varepsilon \quad (1)$$

This formulation allows researchers to make probability statements about the choice of an alternative over others made by the respondent(s) making assumption on the distribution of the error term (Train 2009).

We assume that the deterministic part of utility can be represented by the following three types of attributes: First type, denoted x^{ns} , are attributes that are not influenced by the spatial information and its presentation (e.g. price). Second type, denoted x^{s}, are attributes which are likely to be influenced by spatial information and its presentation (e.g. access, distance). The utility from any alternative in spatially relevant choice situation can be represented as follows:

$$U = sq + \beta x^{ns} + \delta x^{s} + \varepsilon \quad (2)$$

Where β and δ represent associated vectors of preference parameters and sq is a dummy parameter that captures preferences for the status quo option to be estimated. Assuming that the error term follows a Gumbel distribution and parameters are randomly distributed we are able to estimate mixed logit (see the next section) models in preference and WTP space.

We hypothesise that using different spatial representation in choice cards is likely to have a varied effect on the way in which respondents react to each set of attributes. To capture this in the model three vectors α_1, α_2 and α_3 of "spatial framing" effects are included to represent the impact that using the map format has on utility:

$$U = \alpha_1 sq + \alpha_2 \beta x^{ns} + \alpha_3 \delta x^{s} + \varepsilon^{*} \quad (3)$$

Following the error assumption of Eq. 2, the effects of the novel presentation across the treatments requires testing the following hypotheses, assuming NoMap treatment as represented by (2) and Map treatment by (3) above:

$$H^1\colon\ \alpha_3 \delta x^s \neq \delta x^s$$

$$H^2\colon\ \alpha_2 \beta x^{ns} = \beta x^{ns}$$

$$H^3\colon\ \alpha_1 sq = sq$$

We set out to test three hypotheses that can be broadly relevant to numerous context in spatial environmental value assessments. First (H^1), we expect that the Map treatment is likely to have an effect on location attributes and a subset of the remaining attributes. Since the treatment in this study was the presentation of spatial information we expect that the Map treatment will have a pronounced effect on the parameter estimates of location attributes. Further, we hypothesise that the treatment is likely to have an effect on attributes which are influenced by spatial information through an indirect impact on the perception of spatial attributes themselves. Reflecting previous research in the valuation literature, we expect that these attributes will be related to possible use of the site through recreation possibilities which in our scenario are particularly encompassed in the birds and access attributes. Second (H^2), we expect that the Map treatment will not have an effect on the attributes that are not likely to be influence by spatial information and its presentation. We expect these to be size (i.e. scope of intervention) and price attributes. Since the smallest size of the sites presented in the scenarios is likely to be sufficient for recreation opportunities, we hypothesise that the size of the sites will not be influenced by additional spatial information. Finally our third hypothesis, (H^3), relates to the preference for status quo. This parameter captures the preference for the current intense agriculture land use independently by future scenarios of land use changes and we would expect that this preference should not be affected by the use of maps in choice presentation.

3.2 Modelling strategies: mixed logit model in preference and WTP space

The mixed logit (or random coefficients, multinomial logit) model (McFadden and Train, 2000) can closely approximate a very broad class of Random Utility models (ibid). It is used to account for panel structure of the CE data and for the preference heterogeneity within the population. N[th] respondent's utility from choosing alternative i in the j-th choice situation can be represented by:

$$U_{ijn} = V_{ijn} + \varepsilon_{ijn} = \beta_n' X_{ijn} + \varepsilon_{ijn} \qquad (4)$$

where X_{ijn} is the set of explanatory variables observed by the researcher (including alternatives' attributes and respondent's characteristics), is assumed to be iid Gumbel distributed but in this case β_n' represents parameters $(\delta, \beta\ from\ eq\ 2{,}3)$ which are individually specific. Each parameter describes a pre-specified distribution and the objective is to estimates each of these.

Elements of β_n' can be assumed to be either fixed or randomly distributed. One approach for selecting the appropriate "mixing" – i.e. which parameters should be modelled as random and which as fixed – is to use the Lagrange multiplier test (or Z test) approach of McFadden and Train (2000). However, the likely heterogeneous income sensitivity across the population in many cases leads to price parameter being selected as random (and in our case, as reported in the next section). This poses difficulties in deriving WTP values from the mixed logit models estimated directly, in preference space. An alternative to derive consistent WTP values is proposed by Train and Weeks (2005).

In this framework, the objective is directly estimating the WTP values and their distributions, particularly in cases when the price parameter is treated as random in the mixed logit model.

Equation (4) is re-parametrize to derive the WTPs as follows:

$$U_{ijn} = -\beta_n^{price}\left(\frac{\beta_n^{non-price\,\prime}}{\beta_n^{price}} X_{ijn}^{non-price} - X_{ijn}^{price}\right) + \varepsilon_{ijn} = -\beta_n^{price}\left({\gamma_n}' X_{ijn}^{non-price} - X_{ijn}^{price}\right) + \varepsilon_{ijn}$$

where β_n^{price} is the parameter associated with the cost attribute, $\beta_n^{non-price}$ is a vector of parameters for the non-cost attributes, ε_{ijn} the error term and $\gamma_n'$the vector of WTPs for every non-monetary attribute. This model is referred to as mixlogit in WTP-space and is estimated using simulation methods (Train 2009).

Finally, we follow approach of Johnston et al (2016) to test the differences across the treatments, by pooling the two samples together and including a dummy variable for the Map treatment. Pooling the two samples together and estimating the model with the dummy for Maps treatment allows direct testing of the hypotheses set out in section 3.1 above.

3.3 Empirical strategy for assessing the Map treatment

To assess the impacts of the maps presentation (Map treatment in the following text), mixed logit models in preference and WTP-space are estimated and the coefficients from these models are compared through LR tests and through direct comparisons and discussion of the estimated coefficients. Further, the final model allows testing directly the theoretical expectations set out in Section 3.1.

As the Map treatment is applied across different samples of respondents, it is important to test whether the two subsamples (respondents faced with Map and NoMap version of the survey) could be assumed to be drawn from the same populations. Using the t-test and Kruskal-Wallis equality-of-populations rank test, no statistically significant differences on basis of socio-economic characteristics could be observed across the two treatments subsamples that indicates that it is valid to make the claims about the differences between the

Map treatments. The only statistical difference identified across the Map treatment group related to the regions that respondents were from. However, since this treatment is about the cognitive and choice aspects resulting from the different choice set presentation this difference is not likely to be relevant for this treatment.

4 Results

The following section reports the results of the estimated models. Please refer to Table 3 below for definition of each attribute variable used in the analysis alongside their mean values and standard deviations for each treatments. Further, please note that following an exploratory analysis of different distance specification the log(distance) specification was evaluated as best performing and will be used in the analysis reported below as ***ldist***. Similarly, testing the different specifications of the model in terms of the location attributes was estimated, suggesting that an interaction term between country and distance variable should be included.

Table 3 Attribute Descriptions and Descriptive Statistics

Variable	Description & Coding
country	1 = home country; 0 = other country
country_ldist	interaction variable; = country * ldist
ldist	Logarithm of point distance to sites from home location in kilometres
access	1 = access; 0 = no access
size	Size of site; Small=7ha, Medium=150ha, Large=400ha
birds0[10]	1 = **Little or no increase** in the number of birds and wildlife already present in the area; 0 = otherwise
birds1	1 = **Some increase** in the number of birds and wildlife already present in the area; 0 = otherwise
birds2	1 = **Substantial increase** in the number of birds and wildlife already present in the area; 0 = otherwise
birds3	1 = **Substantial increase** in the number of birds and wildlife already present, **Some increase** in the number of species in the area ; 0 = otherwise
birds4	1 = **Substantial increase** in the number of birds and wildlife already present, **Substantial increase** in the number of species in the area; 0 = otherwise
price	The annual increase in water bills for the household (cost of improvements)
sq	1 = if choice is Status Quo; 0 = otherwise

[10] Note that the parameters in the models reported below are estimated relative to a base which in our case was chosen as birds0.

4.1 Mixed Logit models estimated in preference space

Table 4 below reports the results of the mixed logit models estimated[11] for Map and NoMap presentation subsamples. The z-test used in selecting the randomly distributed attributes (McFadden and Train 2000) suggested treating *country*, *country_ldist*, *size* and *sq* parameters as fixed, while *ldist*, *access*, *birds1-4* and *price* to be treated as random, suggesting that there is a preference heterogeneity for these parameters across the sample population. The models allow correlation across the parameters[12].

Table 4 Mixed logit model in Preference Space for Map and NoMap samples

Coefficient	**Maps treatment**		**NoMaps treatment**	
Mean	**Coef.**	**SE**	**Coef.**	**SE**
country	0.455***	0.159	0.048	0.392
country_ldist	-0.071**	0.03	0.079	0.074
ldist	-0.251***	0.026	-0.132	0.064
access	0.746***	0.033	1.029***	0.09
birds1	0.689***	0.046	0.699***	0.116
birds2	1.11***	0.051	1.429***	0.124
birds3	1.446***	0.058	1.729***	0.135
birds4	1.63***	0.062	1.901***	0.154
size	0.0009***	0.0001	0.001***	0.0001
price	-0.019***	0.001	-0.018***	0.001
sq	-2.047***	0.149	-1.212***	0.367
Standard Deviation				
ldist	0.336***	0.012	0.322***	0.03
access	0.964***	0.034	1.141***	0.098
birds1	0.743***	0.065	0.769***	0.198
birds2	1.223***	0.057	1.018***	0.142
birds3	1.544***	0.061	1.195***	0.13
birds4	1.77***	0.063	1.668***	0.144
price	0.018***	0.001	0.018***	0.001
Log likelihood		-22573.1		-3661.08
Number of obs		91728		15696
Number of respondents		1911		327
LR chi2(28)		8549.9		1493.25
Prob > chi2		0.000		0.000
Number of draws used		1500		1500

[11] The models were estimated using Stata, mixlogit (Hole 2007) and mixlogitwtp modules. https://www.sheffield.ac.uk/economics/people/hole/stata

[12] For the coefficient covariance matrix along with their standard errors, please contact the lead author.

Across the two models similar patterns occur for the two treatments. SQ, birds, price, access and size are highly significant and in expected directions. ***SQ*** coefficient is negative suggesting that across the sample population derive utility from changes to status quo of intensive agriculture independently from the attribute levels of such changes. The ***birds*** coefficients are positive and, in line with economic theory increasing with higher attribute levels. Similarly in line with economic theory the ***price*** coefficient is negative. Further, ***access*** attribute is positive. Finally, the ***size*** attribute is positive conforming theoretical expectations (note that the coefficient is associated with 1ha increase in size). For all parameters assumed as randomly distributed, the standard deviations are highly significant, suggesting high level of preference heterogeneity for these attributes across the sample population.

In terms of the impact of maps presentation, it can be seen that the parameter estimates differ across the models. The difference between the two models was confirmed by a log likelihood ratio test for nested models obtained through pooling the dataset and comparing the log likelihood value with that of split models. Further, a clear difference occurs in the significance of the estimated location parameters (***country***, ***country_ldist***, ***ldist***) across the two treatments. While for the Map treatment all three parameters are significant and with expected signs (***ldist*** and ***ldist_country*** negative[13], while ***country*** is positive), in the NoMap treatment ***country*** and ***country_ldist*** parameters were estimated as not different from zero. In both models the ***ldist*** parameter was estimated as negative and in both cases with relatively wide distribution. In both models, significant variation of the ***ldist*** variable suggests different "distance-sensitivity" across the population.

4.2 Mixed logit models in WTP-space

Table 5 below reports the results of the mixed logit model estimated in WTP-space for the Map and NoMap subsamples. These models assume the ***price*** parameter to be log-normally distributed and allow for correlation across the parameters[14]. The model was estimated using 1000 draws for the simulation.[15]. In contrast to models estimated in the preference space, these models allow comparison of the parameters across the two models in terms of the WTP values and their distribution estimated from the two models.

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[13] The interaction term reflects that the negative impact of distance on utility is expected to be more pronounced in respondent's home country.

[14] The means and standard deviations of the price attribute were recalculated from the original STATA output, following Hole (2007).

[15] For the coefficient covariance matrix along with their standard errors, please contact the lead author.

Table 5 Mixed logit model in WTP space for Map and NoMap samples

Coefficient	Maps treatment		NoMaps treatment	
Mean	Coef.	SE	Coef.	SE
country	39.71***	8.72	-8.27	22.70
country_ldist	-7.08***	1.66	5.1	4.16
ldist	-2.07	1.51	-0.97	3.58
access	50.41***	2.20	72.08***	5.76
birds1	68.78***	3.63	70.73***	8.19
birds2	94.52***	3.84	125.71***	8.76
birds3	127.29***	4.56	168.63***	10.93
birds4	140.44***	4.88	184.87***	12.49
size	0.04***	0.00	0.03***	0.01
sq	-54.04***	7.90	-40.46**	21.09
price	-0.03***	0.00	-0.04***	0.00
Standard Deviation				
ldist	17.55***	0.80	15.04***	1.52
access	50.88***	2.00	73.48***	6.97
birds1	53.62***	3.75	54.27***	6.96
birds2	75.94***	3.47	94.34***	8.15
birds3	112.89***	3.87	144.78***	9.55
birds4	124.38***	3.99	166.22***	10.53
price	0.04***	0.00	0.07***	0.01
Log likelihood		-23327.9		-3755.72
Number of obs		91728		15696
Number of respondents		1911		327
LR chi2(11)		23845.12		3721.88
Prob > chi2		0.000		0.000
Number of draws used		1000		1000

Similarly as in the case of mixed logit models estimated in the preference space we see common patterns across the two subsamples. While the WTP coefficient in the NoMap model is not significant at the 0.05 level, magnitudes of the two WTP coefficients suggest that respondents are on average willing to pay positive amounts for improvements to intensive agriculture. The WTP coefficients for birds and access are positive and the highest of all attributes, with birds attribute levels increasing the WTP values. Size WTP coefficient is positive, however relatively small - note that for associated size values presented in the valuation scenarios of small (7ha), medium (100) and large (400) the WTP coefficient needs to be multiplied by associated hectare values. The price coefficients are reported in the preference space, following Hole (2007).

Across the two models we can see differences in terms of the relative sizes of the WTP values estimated – in particular in terms of higher WTP values for ***birds*** and ***access*** in the

NoMap treatment. However, in the NoMap treatment the standard deviations for both ***access*** and ***birds*** are higher than in the Map treatment.

In terms of location attributes, we see even more pronounced difference across the two models than in the previous models. The Map treatment model estimates both ***country*** and ***country_ldist*** parameters as significant and with expected positive WTP coefficients, while the mean of ***ldist*** variable is not estimated to be different from zero. In the NoMap treatment, in contrast, the location attributes were not estimated as significantly different from zero. Both models estimated a wide distribution of the ***ldist*** parameter across the sample populations of a similar magnitude.

4.3 Mixed logit in WTP space with Map dummies

Following approach of Johnston et al. (2016), who analysed the impact of individualised maps on the WTP estimates, we estimated further model on the pooled sample. This mixed logit model estimated in a WTP space includes a dummy interaction indicating the Map treatment (i.e. maps=1 if presented with maps; maps=0 if presented with tabular format) for all but price variable. The interaction variable should hence indicate the difference in WTP term between the Map and NoMap treatments. We selected the same variables as random as in the previous mixed logit models (i.e. ***ldis***t, ***access*** and ***birds***). However, due to significant computational demands for estimating this model in the full form (taking over a month to converge), a simple restriction on the model was implemented. The distribution of all bird parameters were assumed to be drawn from the same distribution. This was represented through a new variable ***bird***, which was defined as dummy being one when any, non-zero, level of bird was presented in the choice situation. This variable was treated as random and represents a joint random coefficient for all bird dummies – its mean value should be interpreted as the mean value of birds1 and a component of the mean values for the rest of the bird dummies. The rest of the bird dummies were treated as fixed – with associated means calculated as mean of bird variable plus mean value for each bird dummy. The standard deviation of the ***bird*** variable represent the distribution characteristic for all bird parameters. While this restriction, indeed, provides not fully complete assessment of the model we believe that it does not hinder the analysis of the effects of the Map treatments, given the consistent similar results of the birds attribute in the previous, separate models.

Please note that the non-interaction attribute coefficients represented WTP values for NoMap subsample and the maps interaction coefficients need to be added to these for the WTP values for Map treatment. This model treats price coefficient common for the two treatments (i.e. with no dummy variable for Map treatment) and as log normally distributed. The model was estimated using 500 draws for simulation and allowed for correlation across the coefficients[16]. The model is reported in the Table 6 below.

Table 6 Mixed logit results in WTP space with a dummy variable for Map treatment

Coefficient	**Maps dummy=1**		**Maps dummy=0**	
Mean	**Coef.**	**SE**	**Coef.**	**SE**
country	31.57	22.61	5.65	20.64
country_ldist	-9.95**	4.30	3.21	3.93
ldist	-7.73**	3.70	5.52	3.37
access	-27.31***	6.14	77.02***	6.03
bird	-24.94***	9.63	109.84***	9.23
birds2	-2.25	4.73	20.37***	4.34
birds3	3.66	5.06	31.61***	4.65
birds4	8.13	5.78	37.43***	5.38
size	0.0006	0.0076	0.0332***	0.0069
sq	-32.14	20.46	-32.49*	18.69
price			-0.02***	0.00
Standard Deviation				
ldist	9.01***	0.78	15.35***	1.72
access	66.92***	5.35	62.1***	5.67
bird	57.63***	6.55	98.08***	8.13
price			0.03***	0.00
Log likelihood			-27671.266	
Number of obs			107424	
Number of respondents			2238	
LR chi2(21)			34541.68	
Prob > chi2			0.000	
Number of draws used			500	

Looking at the results we can see similar patterns as from the two pairs of models estimated on the Map and NoMap subsamples reported above. While the WTP coefficient for SQ is negative across the two treatments, it is not significant at the 0.05 level for neither of the treatments. Access and bird WTP coefficients are positive and with the highest values over all attributes, with increasing values for bird attribute levels. Note that for the mean WTP values for birds2-4 associated mean WTP values need to be added to mean WTP value which represent the mean value of birds1. The WTP coefficient for size is positive and does not differ across the treatments. The price coefficient is reported in preference spaces following approach

[16] For the coefficient covariance matrix along with their standard errors, please contact the lead author.

of Hole (2007). While we see similar magnitude in standard deviation of WTP for access across the treatments, the NoMap treatment shows lower variance for the bird WTP coefficient.

In terms of location attributes, we can again see differences across the two presentation treatments. For the NoMap treatment none locational attributes' coefficient of mean WTP is estimated as significantly different from zero. In case of the Map treatment the mean WTP coefficient for ***country_ldist*** and ***ldist*** parameters are negative, as expected, and statistically significant. In contrast to previous models the WTP coefficients for country attribute is not statistically different from zero.

5 Discussion

The models reported above provide support for the hypothesis that space and its representation matter and that the novel presentation of a map format can possibly improve the preference elicitation for spatial choice experiments. This claim can be supported by the following interpretation of the results reported in the previous section.

First, across the models[17] reported in the paper[18] a clear effect of the map presentation on estimated parameters is present. Consistently across the models a difference between the parameters and WTP values could be seen between the two treatments.

Second, the differences across the models is mostly significantly pronounced in the location attributes (***distance***, ***country*** and their interaction). The location attributes are clearly influenced by the map presentation, however the effects vary across the estimated models. The maps presentation elicits preferences for the presented location attributes – either all three or two of the three relevant attributes are estimated to be significantly different from zero across the three modelling approaches, suggesting that these attributes matter for the choice between alternatives. In the NoMap treatment in all but one instance the location attributes are not estimated to differ from zero (***ldist*** is estimated as different from zero in the mixed logit model estimated in preference space). While this persuasively indicates that the map presentation influences perceptions of spatial context, it is not clear exactly how it influences each of the two location attributes and their interaction. These mixed results indicate an interplay between the two attributes and their interaction which is likely to be result of the experimental design set up and the actual geographical situation in the Great Britain – resulting from under-representation of alternatives that have combination of "less than 60 miles" distance and "other country" combination in the dataset (see Section 2.1.3 for further discussion).

Third, the final dummy model (Table 6) allows for direct testing of the initial hypotheses set out in section 3.1. Recalling the theoretical expectations we expect the map presentation 1) to have an effect on attributes which are influenced by spatial context and its presentation, including the location attributes (H1); 2) not have an effect on attributes not influenced by spatial information and its presentation (H2); and 3) not have an effect on the preferences for status quo (H3). The results of the dummy model – i.e. whether the dummy treatment is

[17] For an overview table of all models reported in this paper, please refer to the Appendix

[18] Please note that the initial analysis also considered Multinomial logit (MNL) model (McFadden, 1974; Louviere et al., 2000) and heteroscedatic multinomial logit models. While the multinomial logit models confirm the differences between the estimates across the treatments, the heteroscedatic model suggests that the no-map version has a higher overall error variance. This supports our hypothesis that the maps presentation is likely to better elicit preferences for spatial choice situations.

estimated as significantly different from zero – provide the ground for these tests. These will be discussed in turn.

H^1: Impact of Map treatment on attributes likely to be influenced by spatial information and its presentation

We see differences across the Map treatment for the two location attributes (***ldist***, ***country_ldist***) and also ***bird*** and ***access*** attributes. This conforms to our initial expectations that the maps presentation will impact on perception of space and that, in turn, will impact on the attributes with high use values component (related to potential for recreation opportunities). Important result here is the impact on location attributes which was the most directly expected impact of individualised map presentation of choice alternatives in comparison to tabular presentation. Interestingly, we can observe that the mean WTP coefficients for ***bird*** and ***access*** attributes are lower for the Map treatment. This is similar with results provided by Johnston et al (2016) who provide possible interpretation that we see similarly. They hypothesise that individualised maps are likely to make respondents more aware of the relative distance to the intervention sites – this effect might be further accentuated in abstract, tabular presentation - causing the respondents to realise that they are not likely to directly benefit (i.e. realise use values) from these sites and hence leading these respondents to exhibit lower WTP values.

H^2: Impact of Map treatment on attributes not likely to be influenced by spatial information and its presentation

In turn, we can see that for the ***size*** attribute, or scale of the intervention, there is no difference across the treatments. This conforms to our expectation that for some attributes the difference in spatial information and its presentation will not have an effect on some of the intervention attributes. This is also true for country attribute, however given the results of the separated models and the difference across the treatments in the interaction variable we cannot decisively suggest whether this attribute is or is not influence by the Map treatment. Since treated the price coefficient as common across the treatment in the dummy model, we could not assess the differences across the treatments through this model. However, from the separated models it is likely that this is the case and will require further investigation.

H^3: Impact of Map treatment on preferences for status quo

Finally, our expectation that the Map treatment will not have an impact on the preferences for status quo is confirmed by the results. However, note that this contrasts to results of the separate models and requires further investigation.

We believe that our approach of presenting choice sets on individualised maps are likely to better portray the spatial information for choice experiments in environmental context. Given the increased ubiquity of the use of mapping software online and on mobile phones (e.g. Google Maps, Apple maps), presenting information in such format is likely to decrease the cognitive effort for understanding the spatial context than in tabular format. We believe that through the map presentation the respondent has more "cognitive energy" for evaluating complex choices which are present in the world and which needs to be valued for policy advice. Further supporting this expectation are the data collected from respondents faced with both formats[19] on their opinion regarding the two formats. On a 7 point Likert scale, 71% percent of the respondents indicated that for answering questions similar to those they answered in the survey they would prefer to see them with maps (see Table below)[20]. Given both respondents' opinion and the results presented in this paper we believe that the individualised map format is likely better elicit preferences and hence strengthen the valuation research in a spatially relevant choice experiments.

Table 7 Respondents' opinion on Map versus NoMap presentation

Opinion on maps presentation	**Number of respondents**	**Percent**
I would strongly prefer questions with maps	134	41 %
…	55	17 %
…	43	13 %
Neither prefer with or without maps	61	19 %
…	15	5 %
…	14	4 %
I would strongly prefer questions without maps	5	1.53 %
Total	**327**	**100%**

However, we are also aware of the many ways our methodology can be improved and it will be the focus of further research. In particular, more flexibility in presenting choice sets could benefit the respondent. For example, further, more detailed, spatial information would make the choice potentially more realistic in providing additional spatial information and context (e.g. actual landscape/satellite map). An ability to zoom and inspect the area a bit closer might, despite requiring a longer time for responding, provide fuller information from the respondent. Similarly, we are aware that the experimental design and how it incorporates spatial information has room for improvement and we hope to develop further additions to this methodology that would accommodate more than two distance categories in the design in the future. Finally our study did not explicitly account for substitutes sites which we see as a major drawback and motivation for further research building on the recent existing literature looking at such issues (e.g. Schaafsma et al. 2013).

[19] Recall that the nomaps treatment respondents were faced at the end of their choice tasks with additional two choice questions they already answered, however this time on a map format.

[20] The exact phrasing of the question was as follows: "If you were to have to answer more questions like those about the sites for land use changes, would you prefer them to have maps or not have maps?"

Finally, in contrast to most of the present CE studies, this research provides some evidence that political boundaries might matter in valuation studies. The country variable seems to play a role in the estimated models, however this role is only seen in the maps presentation. Given that in the tabular format the country where the site would be located was explicitly included in the table of attributes, this result warrants caution regarding the effect of framing. The fact that country seem to matter only in map format might suggest that the maps make the country dimension of location more explicit than in the table only format. While it is not yet clear from the presented analysis how the political boundary matters, this issue warrants further research, due its potential important policy implications. This is particularly true since we are aware of only few studies (e.g. noted Dallimer et al. 2013) that take the political boundaries into account in valuation research.

The results from a survey of a kind presented in this paper can be used to spatially target (land use) interventions to generate greatest welfare impacts. Given the estimated parameters for the location attributes and specific policy scenario (e.g. planting of set hectare amount of woodland in specific region/s of GB), optimal areas could be identified that can generate the greatest benefits for the population distributed across the landscape. This application could take into account socio-economic characteristics of respondents and the available areas for intervention (i.e. reflecting ownership situations), depending on the data available. Indeed, the next step of this research is to develop such analysis that applies estimated value function, which reflects the socio economic characteristics of British population, on scenarios that are developed with stakeholders (e.g. policy makers, farmers, NGOs). Further, this research will be combined with ecological modelling to better account for existing and projected biodiversity in the case study region.

6 Conclusion

This paper presented a novel approach for spatially-relevant choice experiments applied on a case study of assessing preferences for land use change interventions in high intensity agricultural landscapes in Great Britain. It presents a survey instrument that incorporated spatial dimension of choice in different stages of the CE survey development. It explicitly included location attributes in the experimental design and the presentation of the choice set on a spatially explicit map format, while taking into account the actual situation in case study region and respondent's location when generating each choice set. This is the first time, to our knowledge, that a CE study incorporated space in this extent in the design of the survey instrument in the context of valuating environmental related goods and services.

Through application of mixed logit models estimated in preference and WTP-space this paper provides evidence that the individualised map presentation of the choice set is likely to elicit preferences better than traditionally used tabular format of choice set presentation. This adds further evidence to findings of Johnston et al (2016) who tested the impact of individual versus generalised map presentation of choice alternatives in choice experiments. The map presentation has been observed to impact particularly on the location attributes (country where the valued site was, distance to the site and interaction variable of the two attributes), suggesting that the map format elicits spatial attributes better than the tabular format. Further, through estimation of an interaction WTP-space model with the maps presentation dummy variable, the analysis shows that the impact of the individualised maps have effects on attributes likely to be influenced by spatial context, relating to use value motivated attributes. and not having an impact on variables such as scale or preference for status quo.

We hope that the methodology presented in this paper provides useful contribution to the spatial stated preference research and hence contributes to making valuation research ever more relevant and reliable for policy decisions. The application of such methodology might be, for example, used for deriving spatially explicit value transfer function. This is a further focus of our research. In a world of increased environmental pressures (e.g. MA 2005, Rockström et al 2009, Butchart et al. 2010, Pimm et al. 2014, Lenzen et al. 2012), relevant and reliable valuation research is ever more needed for decisions choosing more optimal investments in management of ecosystems, biodiversity and the benefits our society obtains from the natural environment. We hope that potential future research building on the presented methodology might provide better actionable policy advice that brings such decisions closer to everyday reality.

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8 Appendix

8.1 Versions of the survey

	First block of 6 questions	Test	Second block of 6 questions	Test	Other
MAPS 85% sample	Low intensity Agriculture	n/a	Woodland	n/a	n/a
	Low intensity Agriculture	1st question repeated	Woodland	n/a	n/a
	Low intensity Agriculture	n/a	Woodland	7th question repeated	n/a
	Woodland	n/a	Low intensity Agriculture	n/a	n/a
	Woodland	1st question repeated	Low intensity Agriculture	n/a	n/a
	Woodland	n/a	Low intensity Agriculture	7th question repeated	n/a
NO MAPS 15% sample	Low intensity Agriculture	n/a	Woodland	7th question repeated with MAP	1st question repeated with MAP
	Low intensity Agriculture	1st question repeated	Woodland	7th question repeated with MAP	1st question repeated with MAP
	Woodland	n/a	Low intensity Agriculture	7th question repeated with MAP	1st question repeated with MAP
	Woodland	1st question repeated	Low intensity Agriculture	7th question repeated with MAP	1st question repeated with MAP

8.2 Presentation of the attributes in the survey

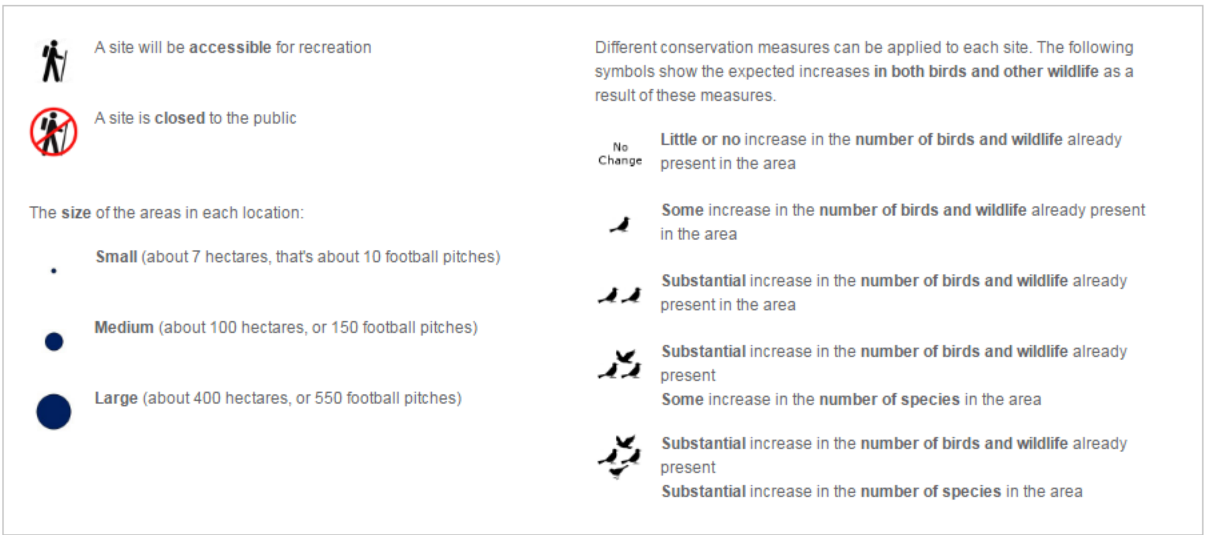

Table 8 All estimated models in one table

Coefficient	Maps treatment		noMaps treatment		Maps treatment		noMaps treatment		Maps dummy=1		Maps dummy=0	
Mean	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
country	0.455***	0.159	0.048	0.392	39.71***	8.72	-8.27	22.70	31.57	22.61	5.65	20.64
country_ldist	-0.071**	0.03	0.079	0.074	-7.08***	1.66	5.1	4.16	-9.95**	4.30	3.21	3.93
ldist	-0.251***	0.026	-0.132	0.064	-2.07	1.51	-0.97	3.58	-7.73**	3.70	5.52	3.37
access	0.746***	0.033	1.029***	0.09	50.41***	2.20	72.08***	5.76	-27.31***	6.14	77.02***	6.03
birds1	0.689***	0.046	0.699***	0.116	68.78***	3.63	70.73***	8.19	-24.94***	9.63	109.84***	9.23
birds2	1.11***	0.051	1.429***	0.124	94.52***	3.84	125.71***	8.76	-2.25	4.73	20.37***	4.34
birds3	1.446***	0.058	1.729***	0.135	127.29***	4.56	168.63***	10.93	3.66	5.06	31.61***	4.65
birds4	1.63***	0.062	1.901***	0.154	140.44***	4.88	184.87***	12.49	8.13	5.78	37.43***	5.38
size	0.0009***	0.0001	0.001***	0.0001	0.04***	0.00	0.03***	0.01	0.0006	0.0076	0.0332***	0.0069
price	-0.019***	0.001	-0.018***	0.001	-54.04***	7.90	-40.46**	21.09	-32.14	20.46	-32.49*	18.69
sq	-2.047***	0.149	-1.212***	0.367	-0.03***	0.00	-0.04***	0.00			-0.02***	0.00
Standard Deviation												
ldist	0.336***	0.012	0.322***	0.03	17.55***	0.80	15.04***	1.52	9.01***	0.78	15.35***	1.72
access	0.964***	0.034	1.141***	0.098	50.88***	2.00	73.48***	6.97	66.92***	5.35	62.1***	5.67
birds1	0.743***	0.065	0.769***	0.198	53.62***	3.75	54.27***	6.96	57.63***	6.55	98.08***	8.13
birds2	1.223***	0.057	1.018***	0.142	75.94***	3.47	94.34***	8.15				
birds3	1.544***	0.061	1.195***	0.13	112.89***	3.87	144.78***	9.55				
birds4	1.77***	0.063	1.668***	0.144	124.38***	3.99	166.22***	10.53				
price	0.018***	0.001	0.018***	0.001	0.04***	0.00	0.07***	0.01			0.03***	0.00
Log likelihood		-22573.1		-3661.08		-23327.9		-3755.72			-27671.266	
Number of obs		91728		15696		91728		15696			107424	
Number of respondents		1911		327		1911		327			2238	
LR chi2(28)		8549.9		1493.25		23845.12		3721.88			34541.68	
Prob > chi2		0.000		0.000		0.000		0.000			0.000	
Number of draws used		1500		1500		1000		1000			500	