The effect of substitutes on preferences of Great Britain population for ecological de-intensification of agriculture

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Abstract

Seeking to inform policy makers of Great Britain (GB) on priority places for incentivizing the shift away from high-intensity agriculture, the paper measures the effect of substitutes on preferences for low intensity agriculture and woodland, and related ecological and recreational benefits. For this, a dataset was collected with a novel methodology that incorporates the spatial nature of goods into the design of discrete choice experiments. In this approach, the options were presented to respondents both in the traditional tabular format and in an innovative personalized map format. To analyse the effects of substitutes on respondents' choices and aggregate willingness to pay, an overview of approaches is provided from the extant literature. Two metrics of substitute availability were constructed from a map classifying intensity of agriculture across whole GB. The effect of substitutes was relevant statistically and avoided biasing downward the estimation of GB population willingness to pay in 30%. In addition, the perception of relative attractiveness of sites was more consistent amongst respondents exposed to maps, attesting the effect of presentation format on preferences for spatially located environmental benefits.

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

Agriculture occupies 68% of GB's land (Eurostat, 2018), and more than half of this share is due to permanent grassland and meadows, attesting a great potential of supplying agri-environmental goods and services (Jones et al., 2015). To seize this potential, agri-environmental policy (AEP) has been conducted since the 1980s, with most of the schemes providing subsidies for environmentally beneficial de-intensification, comprising reduction of stocking rates, agrochemicals usage and woodland expansion (Natural England, 2013). The current orientation pursued by the Department for Environment, Food & Rural Affairs is to increase the schemes' environmental value for money (Gove, 2018, HM Government, 2018, NCC, 2018). What is reasonable in face of evidence that AEP conservation outcomes remain low to moderate after more than ten years of research (Batáry et al., 2015, Schroeder et al., 2012, Couvillon et al., 2014) and it is also connected with the recent trend of changing the target of payments from activities to outcomes (Wynne-Jones, 2013, Reed et al., 2014). Additionally, the anticipated exit from EU's Common Agricultural Policy started a transition towards a reform of AEP. This paper aims to inform and influence this reform process by developing understanding of impact of substitutes on public preferences for interventions in high intensity agricultural lands with positive impact on the environment.

There are two polar ways to increase environmental value for money. The first is focussing on the supply side, changing farmers' incentives to pursue the most ecologically beneficial activities (Armsworth et al., 2012). The second is looking to the demand side and changing geographical targeting of funds to prioritize areas with larger demand for environmental benefits (Bateman et al., 2013). This paper focus on the latter, attempting to map willingness of British public for ecological de-intensification that broadly represent currently implanted AEP in a way which is informative to policy planning and reform of British agricultural policy. For this, two main geographical sources of influences on preferences for land use change are disentangled, distance decay and availability of substitutes (Bateman et al., 2013, Schaafsma et al., 2012). Emphasis in this study is put on the latter, expanding results of a previous study that focused on the effects of choice set presentation on the preferences for the environmental improvements in agricultural lands in GB (Badura et al., 2017[1]). To increase understanding of the two factors, a novel format to present discrete choice experiments was employed by representing alternatives on an individualized map (following Johston et al., 2016) and this was compared to preferences elicited in a traditional tabular format (e.g., Liekens et al., 2013).

Next section present a comprehensive literature review on how substitutes have been incorporated in stated preference valuation research to date. Two major approaches are identified, 'explicit substitutes' approach, that directly includes substitutes in the choice sets and study design and 'implicit substitutes' approach that involves including substitutes post data collection in the analysis stage by researchers. Building on the literature review, section three describes methodological procedures to quantify substitute availability across GB and to measure the substitutes' influence on elicited preferences. The most recurrently used

[1] This paper have been presented at Bioecon 2017 in Tilburg, Netherlands and EAERE 2017 in Athens Greece.

metrics (density and distance) are converted into a set of explanatory variables for choice models. These are estimated with a large dataset from a survey of GB population regarding the shift from high-intensity agriculture towards low-intensity agriculture or woodland (section 4). The results presented in section five reveal that substitutes' effect is significant and seems to be conditioned on the format in which the choice is presented. In particular respondents that were faced with the maps format were, in line with our expectations, influenced with both implicit and explicit substitutes while respondents faced with tabular format were not influenced by either. This result is significant, and will help to provide better policy advice for spatial targeting of AEP for environmental public goods as the current Government aspires for (HM Government 2018). In fact, "getting the presentation format right" could avoid considerable planning errors, as the effect of substitutes' was not only sensitive to presention format but also significant as a driver of the aggregate willingness to pay of whole GB population. A discussion coupled with conclusion closes the paper.

2 Literature review

2.1 Three main questions

The issue of substitution was emphasized by many papers as crucial for proper estimation of willingness to pay (WTP) for spatially located goods (Bateman, 2009, Schaafsma et al., 2012, Cummings, 1995). One of the main reasons seems to be the fact that spatial goods are highly interdependent (Hunt et al., 2004). This literature review focus on how stated preference research answers three main questions:

1. What is a substitute?
2. How to measure substitutes?
3. How to introduce substitutes in valuation?

2.2 What is a substitute?

The main question of Cummings (1995) is how to select "relevant" substitutes. Or, to put differently, how to define the range of goods individuals understand as substitutes to the good targeted by valuation. Author's discussion focus on delimiting substitute environmental policies and it opens up a demarcation problem, i.e., a "where to stop in including substitutes?". The practical relevance of this issue is attested by Cummings (1995) findings that (i) two "dissimilar" environmental policies (the preservation of fish and the development of a new green park) were seen as substitutes by respondents and (ii) a non-environmental policy (reducing the response time of local fire department) was seen as substitute to environmental policies.

What shows that the most intuitive answer to the "which?" question, that is, similarity, is not necessarily sufficient, whether its meaning is not precisely defined. Researchers and respondents may differ in the notion of similarity they apply to the object of valuation. In the case of Cummings (1995), respondents seemed to have a broader definition that ignored the "environmental/non-environmental" categorization and also the categorization of types of environmental goods (fish/green space).

However, the question of the relevant set of substitutes or notion of similarity has not been much discussed in the recent literature. Three exceptions were found. First, Schaafsma et al. (2013), in which respondents' and researchers' defined substitute sets did not "entirely overlap"[2], in line with Cummings (1995). Second, Schaafsma et al (2012) claimed that incorporating directional covariates in WTP function, in order to capture uneven distribution of substitutes within a distance, avoids the task of selecting relevant substitutes. This can be interpreted as the strategy of capturing a reasonable number of potentially relevant substitutes and then leaving for data to show whether captured substitutes actually affect respondents' choices or not. Third, Jorgensen et al. (2013) wonder whether the result of larger effect of substitutes for non-users was due to the fact that substitutes considered "may not in fact be perceived as relevant substitutes by many users".

Notwithstanding the few papers discussing the issue, the "similarity of what" question cannot be ignored. On table 1, the term "specific class" indicates similarity on apparent characteristics of goods. This is the notion of similarity generally employed by researchers. Any broader notion is referred as "similarity in general class" (the case of the policies of Cummings, 1994 and Neill et al., 1994). The former notion of similarity was more recurrent (9 of 16 papers) than the latter (2 of 16 papers).

There were also five papers that further refined the "specific class" notion. Schaafsma et al. (2013) combined specific class similarity with similarity in functionality, as only water sites with at least one of three recreational functionalities were seen as substitutes. Bateman et al (2008) and Jorgensen et al (2013) further refined water substitutes in water type (fresh and salt). Czajkowski et al. (2017) refined forests by arboreal class (coniferous, deciduous, mixed), age (area of forest aged > 120 years) and species diversity (area of forest with more than 6 tree species). A similar refinement was used by Liekens et al. (2013). Meyerhoff et al. (2013) refined substitute wind turbines (seen as externalities' sources) by whether they belonged to wind farms. Which, in a more general perspective, means refining goods by whether they are clustered or not.

In sum, the main notion of similarity that prevails in recent literature is mainly visual or intuitive, with goods that look alike being classified as similar with some further refinement based on characteristics that are also intuitive or useful for a given application (salt water and fresh water, arboreal classes of forests, etc). Also, similarity is generally defined by researchers. These two guidelines are followed in this paper.

[2] Respondents were asked to list sites they commonly visited, what activities they do on them, what they would do if water qual. fall enough to prevent provision of the 3 functionalities on most visited of the 3 sites pre-defined (the latter seems to be a measure of substitute relevance). This was complemented by two sets of similarity/policy applicability criteria used for researcher-selection of sites.

Table 1 Classification by substitution identification criteria (what?)

Category	N	Papers
Similarity in general class	2 of 16	.Cummings (1994): similarity in general class of good (two environmental and one non-environmental policies); .Neill (1995): similarity in general class of good (eight environmental goods going from fish, water, contamination, waste, health and safety, water and air pollution).
Similarity in specific class (not further refined)	9 of 16	.Schaafsma and Brower (2013): similarity in specific class of good (11 lakes); .Schaafsma et al (2012): idem; .Pate and Loomis (1997): similarity in specific class of good (all state-level wetland sites, all state-level salmon population) [all sites and salmons, no matter the distance from respondent; however distance effect was partially controlled for, based on subdivisions of states]; .Lizin et al (2016): similarity in specific class of good (two pre-defined water bodies). .Valck et al (2017): similarity is specific class of good (green or unmanaged (natural) land parcels [the three sites valued were also considered in the substitutes metrics]) .Sagebiel et al. (2015): similarity is specific class of good (LUC); .Sagebiel et al. (2017): similarity is specific class of good (all forest within 15 km of respondent); .Morse-Jones (2012): similarity in specific class of good (two pre-defined sites of biodiversity overseas [tropical sites valued by UK residents]); .Meyerhoff et al. (2013): similarity in specific class of good (three wind power expansion programmes for Westsachsen region of Germany).
Similarity in specific class (further refined)	6 of 16	.Schaafsma et al. (2013): water recreation sites: three in design and nearest sites in analysis; similarity defined in functional terms, i.e., only sites with one of three functionalities (walking, swimming, nature appreciation) where deemed as substitutes; .Jorgensen et al. (2013): similarity in specific class of good separated by sub-specific class (water bodies of fresh water and salt water (coast)); .Bateman et al. (2008): idem; .Czajkowski et al. (2016): similarity in specific class refined by good type [forest type in aboreal class, age and diversity (area of forest with at least six tree species)]; .Liekens et al. (2013): similarity in specific class of good refined by good type [type of natural area: pioneer vegetation, mudland and marshes, grassland, forest, swamps and heathland]; .Meyerhoff et al. (2013): similarity in specific class of "bad" (turbine, which causes disutility), refined by good type [whether turbine belongs to a wind farm].

2.3 How to measure substitutes?

The most recurrent metrics for substitute availability were (i) amount (or abundance) of substitutes, (ii) number of alternatives in choice sets of choice experiments and (iii) distance to the nearest substitute (non-directional and directional; details on Box 1). Regarding the second class, Morse-Jones et al. (2012) incorporated multiple goods in choice sets (CS) with the use of specific attributes. Regarding the distance metric, Bateman et al. (2008) and Jorgensen et al. (2016), which focused in water valuation, used a refined distance metric that discriminated type of substitute. A similar procedure was pursued by Meyerhoff et al. (2013) in which characteristics of nearest wind turbines were accounted for in WTP function. Only Schaafsma et al. (2012 and 2013) considered direction rather than just distance.

Pate and Loomis (1997) employed a quantity metric in which all wetland sites and salmons within respondents' state of residence were accounted as substitutes. Abundance/density metrics were also used by Czajkowski et al. (2016) consisting in share of forest of different arboreal classes, age and diversity. Valck et al. (2017) employed a density metric based on circular buffers around respondents. Ten distances were considered and the shares of substitute site areas in each buffer were weighted according to four functions of distance. Sagebiel et al. (2017) incorporated the share of forest within 15 km of residents in the WTP for afforestation and Liekens et al. (2013) opted for a green space per capita metric calculated within 20 km buffers of respondents. Meyerhoff et al. (2013) counted the number of turbines and turbine clusters (wind farms) within 5 km of respondents.

Only three studies tested for the effect on WTP of different substitute availability metrics, Schaafsma et al. (2012 and 2013) and Meyerhoff et al. (2013). Schaafsma et al. (2012 and 2013) results showed that directional metrics adds to the traditional one-dimensional distance metric. After controlling for distance, WTP varied with direction between respondents and sites. In fact, Schaafsma et al. (2012) found strong evidence of effect of metric on WTP aggregation. WTP for lake improvements was 32% higher after accounting for directional effects for one of the eleven lakes valued and 29% lower for other lake. That such directional effects were capturing substitute availability was confirmed by stronger effects across directions with more substitutes. The metrics that Meyerhoff et al. (2013) significantly captured distance and characteristics of nearest turbines. The density metric, number of turbines within 5km, and also whether the turbine belonged to a wind farm were not significant.

A scarcity effect was evidenced by the three-stage approach of Czajkowski et al. (2016) in which CE-estimated WTPs were inputted into a spatial autocorrelation model with forest scarcity and distance decay covariates. WTP was negatively related with areal share of forest types in respondent location (a 10 x 10 km cell). Authors claim such effect was due to satiation (decreasing marginal utility) or to congestion externalities of improvements valued[3].

[3] However such scarcity effect may not capture a substitution effect as the good offered was a policy that would affect equally all forests of the country. A substitute to that would be a different federal-level policy and not forests around respondents as those are also subjected to the provision change valued.

Liekens et al. (2013) found that the type of land use which is adjacent to a nature site altered WTP for the site. Adjacent nature land uses increased average WTP in €10/household/year, residential adjacent land uses increased in €8/household/year and industrial land uses decreased in €15/HH/year. The authors *en passant* argue that adjacent land use may "partly capture substitution or scarcity possibilities".

In sum, the number of alternatives in the choice set was use in majority of papers and, regarding metrics introduced in the analysis stage, abundance and distance metrics were the most recurrent. These were the three metrics considered in this paper.

Box 1 Classification by availability metric (how to measure?)

1 Amount of substitutes within a spatial domain (7 of 16)

a) Pate and Loomis: quantity of goods of the class valued [state level, wetland area and salmon population]
b) Valck et al. (2017): share of sites' area in circular buffers, summed across ten buffer distances. Alternative metrics differed in weighting by inverse distance (not weighted, inverse distance, inverse squared distance, log (1+distance)). Only squared inverse distance had significant effect;
c) Czajkowski et al. (2016): the paper does not claim to use a substitute metric, however the forest scarcity metric may be used in other applications as a substitutes availability metric. The scarcity metric is the areal share of forest types in the 10 x 10 km cell respondents are located
d) Sagebiel et al. (2015): substitutes available within 15km of residence were measured in basis of (i) share of forest, (ii) average size of forested patches and (iii) biodiversity. However, non-conservation sites (supposedly, non-substitutes) were also accounted for (average size of agricultural fields, share of area planted with corn and share of grazing area (meadows)) [note: this paper is not clear in which is the good valued, whether LUC towards forest or a generic LUC].
e) Sagebiel et al. (2017): only similar substitutes were accounted for (only forest share within 15km is accounted for in the WTP function for afforestation);
f) Liekens et al. (2013): it was included in early estimation of WTP function a density measure of "green space" per capita within 20km of respondents' residences which was not significant [the exact formula of the metric is not detailed];
g) Meyerhoff et al. (2013): dummy for more than 2 turbines within 200 m, number of turbines in the farm if the nearest turbine belongs to a farm, number of turbines within 5 km, number of wind farms within 5 km.

2 Number of alternatives in the choice set (7 of 16)

a) Schaafsma and Brower (2013): small CS (4 nearest sites among 11) and large CS (7 random sites from 11)
b) Lizin et al. (2016): 2 labelled alternatives [2 water bodies]
c) Schaafsma et al. (2012): 7 sites as alternatives in CS together with maps with all sites (11)
d) Schaafsma et al. (2013): 3 alternatives in CS

e) Morse-Jones et al. (2012): single-site and double site CSs were offered which differed in number of attributes (and not number of CS alternatives)
f) Liekens et al. (2013): alternatives in CS, which could be, however, very different in terms of (a) size of good [area], (b) type of good ["nature" site type, not necessarily forest];
g) Meyerhoff et al. (2013): 3 alternatives in CS.

3 Number of goods in contingent valuation

a) Cummings et al. (1994): number of goods valued [1 to 3, combinations were randomized across respondent]
b) Neill et al., 1995: number of substitutes informed and number of substitutes valued

4 Euclidian distance/travel distance /travel time to nearest substitute (non-directional) (4 of 16)

a) Lizin et al. 2016: distance to other good (two pre-specified goods only);
b) Jorgensen et al., 2013: travel time to two types of substitutes, fresh water bodies and coast (salt water);
c) Bateman et al., 2008: idem;
d) Meyerhoff et al. (2013): distance to nearest turbine and characteristics of nearest turbine (height, rotor diameter, installed power, turbine age).

5 Directional (travel) distance to nearest substitute (2 of 16)

a) Schaafsma et al. (2012): distance and direction from the good of the alternative [distance and direction to the 10 substitutes were not accounted for as covariates in the model; only distance and direction to the own-good]
b) Schaafsma et al. (2013): direction distance measure with latitudinal and longitudinal distance, as well sine and cosine of the angle between site and respondent (cosine and sine)

6 Substitute clustering (1 of 16): Liekens et al. (2013): it is *en passant* argued that the attribute "adjacent land use" could capture [local] substitute availability.

2.4 How to introduce substitutes in valuation?

Three ways to introduce substitutes in valuation were detected.

1. Reminding respondents of the existence of substitutes (3 of 16 papers). “Passive” and “active” ways to remind may be distinguished. The former consists in statements that substitutes must be accounted for to declare WTP and the latter in warm-up questions in which respondents are led to think about their preferences regarding substitutes. This “passive” way was proved non-effective in the 90’s by Neill (1995) and Loomis et al. (1994) and not recent paper testing it was found. However, regarding the “active” approach, Schaafsma and Brower (2013) speculate, in trying to explain the null effect of large CS compared to small CS, whether warm-up questions on all substitutes of the study region made irrelevant the information CSs with 7 alternatives added to CSs with 4

alternatives. Anyhow, the “reminder” approach was the least recurrent in reviewed literature;

2. Explicit introduction in design, complemented by explicit valuation (of substitutes; 10 of 16 papers). Cummings et al. (1995) used this approach in a contingent valuation study of public policies. In the more recent papers reviewed, in which choice experiment is the dominant valuation technique, introduction in design takes the form of choice set alternatives offered explicitly as substitutes (eg., Schaafsma and Brower 2013). This approach was named “explicit substitutes” by Lizin et al. (2016);
3. Implicit introduction in data analysis. Ten papers introduced substitute availability only in analysis, i.e., in the WTP function, thus assuming respondents spontaneously accounted for them; an “ex-post” (Lizin et al. 2016) or “researcher-defined” approach (Schaafsma et al. 2013).

The “design” approach may be limited by preference inconsistencies. Schaafsma and Brower (2013) tested for substitute availability effect on WTP by comparing choice sets (CS) with 4 (small) and 7 (large) alternatives – they also tested for preference stability re-offering small CS after large. Results showed no difference in coefficient and WTP estimates but only in variance (precision) which was larger for large CS. This corroborates authors’ insight of a dilemma inherent to selection of choice set size. Too small CSs violate the axiom of completeness, too large may impose a cognitive burden faceable only with non-rational rules-of-thumb. In both cases, preference consistency is violated.

A hybrid of the design and analysis approaches was explored by Sagebiel et al. (2015 and 2017). Authors combined the offer of generic status quo substitute levels in the opt-out alternative with measured status quo levels introduced only in analysis. Morse-Jones et al. (2012) used a different hybrid strategy. First, they split the sample in groups receiving single-site and double site choice sets and then, in analysis, choice set type effect was tested with interactions of choice set type dummy and attributes of good valued (biodiversity sites). With this, they managed to identify substitution and complementarity effects between sites. Also, interestingly, whether substitution or complementarity prevailed depended on the type of good (endemic species were complementary and non-endemic were substitutes, as expected). Meyerhoff et al. (2013) accounted both for multiple good provision programmes in choice set and for availability of substitute goods in ex-post fashion.

Hunt et al. (2004) claims that econometric models such as the mixed logit are able to capture the complex substitution patterns spatial alternatives are by nature subjected to. The authors’ argument can be interpreted as a defence of the “design” approach, as substitution relationships are captured by the relative utilities of alternatives. However, as already mentioned, the “design” approach is limited by the cognitive burden of large choice sets (Schaafsma and Brower, 2013). Therefore a most practical approach would be a hybrid of "design" and "analysis" approaches, in which the largest feasible number of alternatives is added to choice sets (perhaps randomized across choice sets or choice set blocks) and this is completed with implicit substitutes included in analysis stage. This is the path pursued in this paper.

3 Method

3.1 The Discrete choice experiment (DCE)

The DCE valued land use change from high-intensity to low-intensity agriculture or woodland, and associated conservation and recreation benefits. A total of 2,238 respondents across whole Great Britain were randomly selected to fill an online questionnaire. They were exposed to twelve choice sets of four alternatives each. In three of the alternatives, a specific site was changed, with no change occurring in the fourth, status quo option. Attributes are shown in table 2 and for details on attribute selection and design the reader is referred to Badura et al. (2017). Differences between the final land uses were illustrated with images selected with expert advice and their understanding was checked with a quiz.

The main methodological goal of the DCE was to measure the influence of the choice set presentation format on choices. A new format, consisting in a GB map highlighting location of offered sites, respondent location and countries boundaries (offered to 1,911 respondents), was compared with the traditional tabular format (offered to 327 respondents, Badura et al., 2017).

Table 2 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

Source: Badura et al., 2017.

3.2 Econometric analysis

To test the hypothesis that substitute availability influenced land conversion choice, two types of substitutes were considered, explicit, which were offered as alternatives within choice sets and also represented on maps, and implicit, understood as similar sites detected by researchers and introduced only in the analysis. The following functional form was taken as basis for modelling choices (Greene e Hensher, 2010):

$$Y_{ij} = F(A\Gamma + \lambda_1 dist\_other_j + \lambda_2 dist\_site_j + \lambda_3\ abu\_site_j + \lambda_4 d\_SQ_j abu\_resp_i + \lambda_5 d\_SQ_j Z_i \Theta)$$

With "i" indexing respondent and "j", the alternative, "Y" being a binary variable indicating whether the alternative was chosen, "A" being the vector with choices' attributes (country, distance to site, access, size, birds, woodland dummy) and the explicit substitutes being synthesized by "dist_other", the distance to the nearest other site offered in the choice set. Implicit substitutes were introduced by "abu_site" and "abu_resp", the abundance of substitutes around, respectively, site and respondent. Other variables are d_SQ ≡ status-quo dummy and Z_i ≡ vector of respondent-specific variables (income, user status, education and a unitary constant). The function F(.) has a logistic specification for the mixed logit (Train, 2003, chap. 6.1).

This approach of testing multiple substitute metrics in a single model was inspired in Schaafsma et al. (2012 and 2013) and Meyerhoff et al. (2013). The "other site" metric was inspired in Lizin et al (2016). Two hypotheses tests of interest are detailed in what as follows.

The first, which refers to explicit substitutes, is of the form H0: $\lambda_1 = 0$ vs H1: $\lambda_1 > 0$ (T.1). The intuition for this test comes from the implicit assumption that the three sites in each choice were potential substitutes for each other. Let the idea of quality of a good be taken as metaphor for site-respondent proximity and be reminded that the test attempts to check for existence of substitution effect between three "goods" (sites). Thus, the test is just like the experiment of decreasing quality of two goods while keeping the quality of the third unchanged ("dist_site" is controlled for) and observing whether demand for the third increases[4].

The second test, which refers to implicit substitutes, is H0: (no substitute effect) $\lambda_3 = \lambda_4 = 0$ vs H1: (substitute effect) $\lambda_3 < 0$, $\lambda_4 > 0$ (T.2). It should be noted that the effect of abundance around respondent is positive due to the interaction with the SQ dummy, what makes λ_4 captures the effect on the probability of choosing the SQ - such interpretation of interactions between respondent-specific variables and alternative-specific dummies in mixed-logit models is in accordance with the literature (Schaafsma et al., 2013, Lizin et al., 2016 and Villanueva et al., 2016, Kuhfuss et al., 2015).

Alternative specifications of the two tests were also attempted by an expansion of the functional form for interactions between a binary for whether respondent was confronted with map presentation format ("d_maps") and substitutes' metrics. These tests captured whether map presentation influenced sensibility of choices to distances and substitutes, expanding the results from Badura et al. (2017). Four models were estimated. The baseline model without

[4] This is fully in accordance with the microeconomic definition of substitutes, which stablishes a relationship between (i) demand for a good and (ii) characteristics of other goods.

substitutes' metrics (model 0), the baseline model augmented by substitutes' metrics (model 1), the previous model augmented by interaction with presentation format dummy (model 2) and a model with substitutes' metrics and based only on the subsample exposed to map presentation format (model 3).

Estimation was pursued with WTP-space mixed logit models (Hole and Kolstad, 2012). The Mcfadden and Train (2000) test was applied, with the procedure recommended by Brownstone (2001), to identify which coefficients of attributes should be treated as random, in order to save on computation time (which grows with number of random parameters, Hensher et al., 2005, section 15.4).

3.3 Substitutes' metrics

Implicit substitutes were measured at the 2 km resolution level of the Agricultural Census of 2011 (more details on Bateman et al., 2013). Land use classes were aggregated into (i) arable, (ii) grassland, (iii) woodland, (iv) urban and (v) water bodies and coastline. Substitutes are understood as pixels classified as low-intensity agriculture (LIF) or woodland (see section 4.1 below). Two metrics of substitute availability were adopted, (i) distance to the nearest substitute and (ii) spatially-discounted density of substitutes. The particular specification of this second metric comes from Valck et al. (2017), being:

$$density = \sum_{j=1}^{7} \frac{a(r_j)}{\pi r_j^2} \frac{1}{r}$$

With $a(r_j)$ being the total area of substitutes within a r_j radius of the reference. Radius considered were r_1 = 1km, r_2 = 2.5km, r_3 = 10km, r_4 = 25km, r_5 = 50km, r_6 = 75km, r_7 = 100km (length is specified in hectometres, 10^2 m, and area in hectares). The denominator area, πr^2, is the total area spanned by the radius[5].

The two metrics were calculated having the location of both DCE respondents' and sites offered as references. However, as SQ alternative did not referred to a particular site, but, in fact, to all three sites of non-SQ alternatives, the value for SQ's substitute metrics were assumed to equal the average across non-SQ alternatives of each choice set.

Previous studies detected redundancy in landscape metrics similar to the ones here considered (Cushman et al., 2008). Also, a significant correlation of at least 40% was observed for the two metrics. Redundancy, also known as multicollinearity, leads to the type II error of not rejecting the null hypothesis that one of the metrics have no effect on choice, even if it actually does (Gujarati, 2003, chapter 10). Greene (2003, p.57) states that one of the potential symptoms of multicollinearity is point estimates presenting signs different from the expected. Even with other econometric textbooks restricting implications of multicollinearity to variance of estimators (Wooldridge, 2002, chap.3, Gujarati, chap.10, Baltagi, 2011, chap.4), the point made by Greene (2003) calls for caution in relying on the signs of estimates subjected to multicollinearity. Therefore, to eliminate redundancy, the two metrics were synthesized into their first principal component. This is hereafter reference simply as

[5] In fact this underestimates total area of the cells within r_j, as the pixels are squares, so with their centroids taken as reference, a given radius will span a circumference and also the portions of the farthest squares which are beyond the circumference line.

"abundance" as it was positively related with the density metric and negatively with the distance metric.

3.4 WTP map

To map the aggregate willingness to pay for land use change of GB population, the original resolution was reduced from 2km to 10 km, to keep memory requirement of computation feasible. The average individual WTP of the population located in the i-th cell for the shifting of j-th cell's high-intensity agriculture to woodland or low-intensity agriculture was calculated with formula below[6].

$$WTP_{ij} = \gamma_1 d\_country_{ij} + \gamma_2 \log(dist_{ij}) + \gamma_3 access + \gamma_4 birds + \gamma_5 size_j + \gamma_6 \log(dist\_sub_i)$$

With γ. being coefficients estimated with the choice model. The variable d_country is a dummy that takes unitary value if the j-th site-cell and i-th population-cell are located on the same country. The Euclidian distance (in km) between "i" and "j" is represented by "dist" and the area of high-intensity agriculture in site-cell "j" is indicated by "size". Such area was assumed to equal a particular DCE level or to match the effective arable land in each j-th cell. The distance to the substitute site which is nearest to i-th cell is represented by "dist_sub". The variables "access" and "birds" were assigned with the same levels for all cells. For the former, a unitary value was used to indicate all sites would be publicly accessible after conversion. The aggregate WTP at site level is:

$$AWTP_j = \sum_{i=1}^{I} pop_i WTP_{ij}$$

Which is the WTP of whole GB population for shifting j-th cell from high-intensity farming to woodland or low-intensity farming. It should be highlighted that "pop_i" is the population of individuals of i-th cell divided by GB's average household size (as the price attribute of the DCE was meant to be a household contribution).

In order to avoid extrapolating the sample excessively in terms of distance between respondent and offered site, only sites within the threshold distance of 200 km of each populated cell were considered for the WTP map. Such threshold captures 70% of alternatives offered to respondents (table 3).

Table 3 Statistics for respondent-site distance, DCE sample

OBS	Mean	SD	Min	Max	p50	p75	p90	% ≤ 200km
107,424	154.06	167.59	0	917.32	96.56	233.35	410.38	69.76%

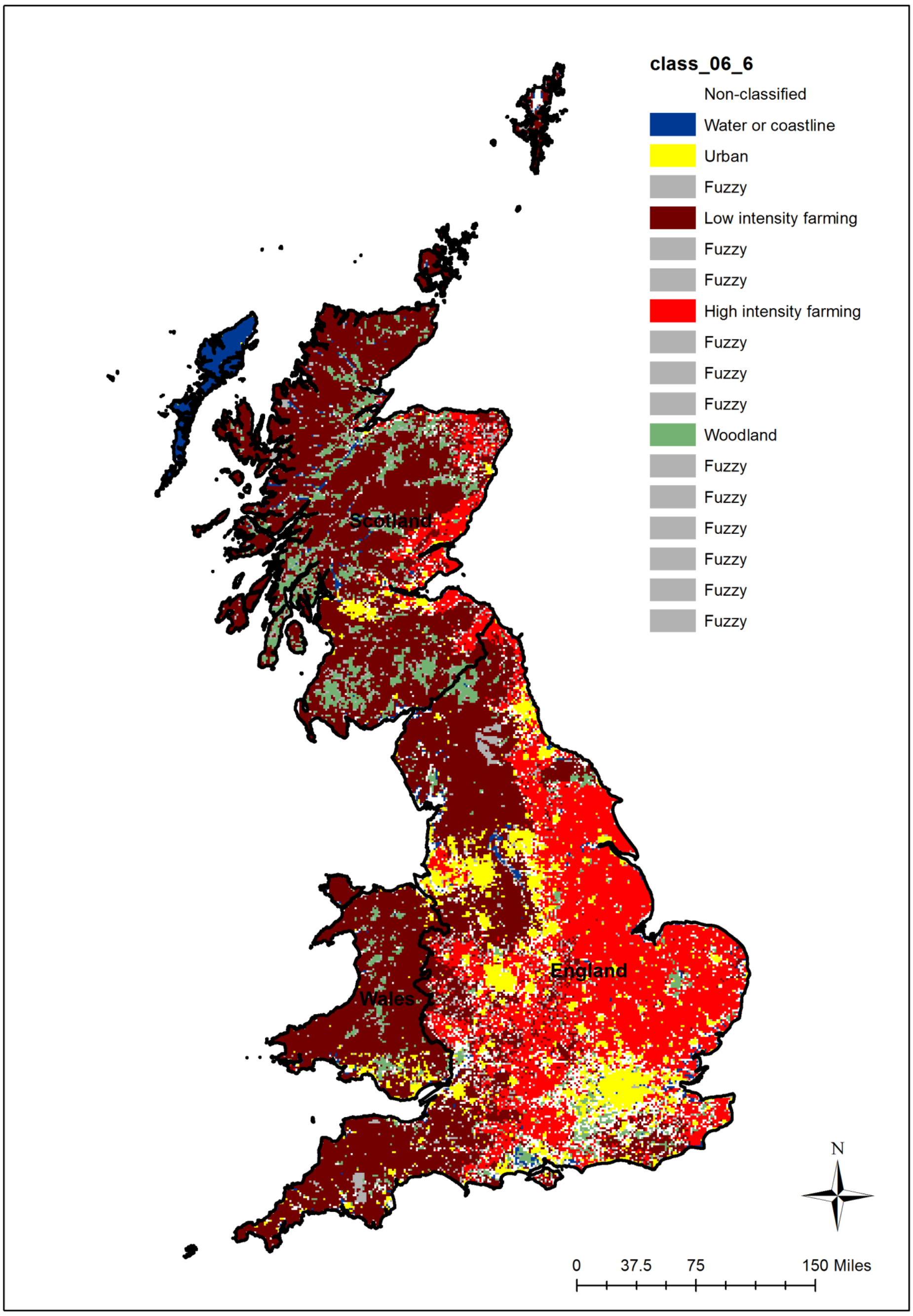
6 This formula is obtained from the first-principles approach of Bockstael et al. (2007) and Train (2003, chap. 3.5) whether the goal is to calculate the compensating variation in income that would make ith-cell population indifferent between shifting and not shifting.

4 Data

4.1 Mapping of substitute land uses

Figure 1 shows the land use classification developed to base assessment of substitute availability. By “high-intensity farming” it is meant the pixel is dominated by arable. “Low-intensity farming” means domination by grassland, and likewise for “woodland”, “urban” and “water or coastline” classes. The procedure used to determine whether a particular land use was dominant or not at each cell is detailed in appendix A. Only cells classified as “low-intensity farming” and “woodland” are here considered as substitutes (to the sites offered in the DCE). It should be reminded that this classification was made at 2 km resolution.

Figure 1 Land use classification for substitute availability assessment (substitutes are green and brown coloured pixels)



4.2 Other variables: population, location of respondents and offered sites

Population data comes from National Aeronautics and Space Administration (NASA) gridded population, which, for the case of GB, was based in the 2011 Census of the three countries (England, Wales and Scotland; NASA, 2018). The original resolution of the data, 1km, was reduced to 10 km for computation of aggregate WTP.

The two components (outward and inward) of respondents' postal codes from the DCE database were combined with the National Health System (NHS) postcode directory, assembled by the Office for National Statistics (NHS, 2017). The latter informed the 1m-resolution latitude and longitude for 2,601,159 postal codes, making it possible thus to georeference postal codes declared.

Only 63 of the 2,238 respondents could not had their postcode related with NHS database, either due to partial of full omission of inward code (second part of postcode) by respondents or due to the postcode being missing from NHS database. For these respondents, the latitude and longitude of the 2km grid cell their residency fell into were taken as basis. Two NHS directory's versions were tested, November 2016 and August 2017. They proved equal in the list of respondents' postcodes not matched and the most recent was then taken as basis for being more updated.

Sites offered were randomly sampled cells of the same 2 km grid used to identify substitute sites, thus their location were automatically available.

The definitions and statistical summary of choice model's variables are found in table 4 below.

Table 4 Definition and summary of variables

Variable	Definition	Mean	Std. Dev.	Min	Max
Distance to competing sites	Distance to the nearest other site offered in the choice set (explicit substitutes)	4.42	0.60	2.09	6.48
Substitutes at site	Abundance of substitutes around offered site (implicit substitutes)	0.00	1.20	-7.17	1.90
Substitutes at respondent	Abundance of substitutes around respondent residence (implicit substitutes)	0.00	0.59	-4.88	4.68
Woodland?	Is woodland the final land use for the site offered?	0.13	0.33	-	1.00
Income	Household income	754.31	1,597.90	-	7,500.00
Frequent user?	Visit the site at least monthly?	0.10	0.30	-	1.00
Higher education?	Education at least first-high degree?	0.10	0.30	-	1.00
Maps?	Exposed to maps format?	0.85	0.35	-	1.00

Note: DCE attributes are omitted and the reader is referred to table 2.

5 Results

5.1 Choice models

Table 5 below reports estimates from four choice models. Based on the whole sample, of all substitute metrics used in our models, only the metric aiming to capture explicit substitutes (T.1) was significant and had the expected positive sign. This indicates that the farther other sites in the choice set were, the higher was the probability of choosing the given site (models 1 and 2 of Table 5). We estimated the metric aiming to capture abundance of implicit substitutes (T.2) as significant and with expected positive sign only for the subsample exposed to the map format only (model 3).

Our results suggest that the map format increased sensitiveness to explicit substitutes (T.1) as revealed by the significance of the interaction between distance to the nearest explicit substitute and maps dummy (table 5, model 2). This suggests that the visualization on map made more precise not only the perception of sites individual attractiveness (what was already attested in Badura et al., 2017), but also of their relative attractiveness. What this means is that relative attractiveness was more coherent with theory under the map presentation format. This last result was evidenced by a significant and positive effect of distance on explicit substitutes interacted with maps dummy, while without the interaction this effect was found negative or insignificant (model 2). In consonance, explicit substitutes interacted with maps dummy had larger significance (model 2) as compared to explicit substitutes alone in the model without maps dummy interactions (model 1). Further evidence reflecting the difference across the two formats was brought by the estimation of model only on the sample exposed to maps format (model 3). In such case, both explicit substitutes (T.1) and abundance of implicit substitutes around respondents (T.2) were significant with expected signs (i.e., null hypothesis was rejected in both T.1 and T.2).

In addition, it was within the maps subsample (Model 3) that estimation fitted best the data. This model showed the lowest levels of Akaike and Bayesian information criteria (AIC and BIC)[7] across all four models, an indicator commonly used for model selection. It should also be noted that, with the whole sample, accounting for substitutes improved only marginally model fitness. But, when presentation format was also accounted for, a larger improvement in the AIC and BIC criteria was achieved.

In sum, substitutes proved influential on choices for shifting to low intensity agricultural land use in GB, with the null hypothesis of the two tests set out in Section 3.2 being rejected. Further, the willingness of GB population to pay for converting a particular site decreased with proximity to other sites, that were offered as alternative places where shifting could happen, and with proximity to sites already occupied by low intensity land use. This effect was observable when choices were presented on individualised maps, however, it was not present in a tabular format.

[7] Calculated as AIC = -2ll +2k and BIC = -ll +k/2.ln(N), with ll = log-likelihood, k = number of parameters, N= number of observations (Boxall and Adamowicz, 2002).

Table 5 Estimation results

Variable	Model 0	Model 1	Model 2	Model 3
Country	3.2101*	4.2680**	3.4759*	8.5524***
	[1.5685]	[1.4942]	[1.4120]	[2.5673]
Distance to site	-8.2699***	-11.1966***	-9.4866**	-10.6047***
	[0.9227]	[2.1863]	[3.4738]	[2.9151]
Access	59.1907***	55.7425***	62.2888***	53.7681***
	[3.5900]	[3.1499]	[3.3112]	[3.0642]
Birds1	76.2360***	81.4230***	88.7312***	64.5150***
	[6.3725]	[4.3078]	[5.1348]	[3.6926]
Birds2	113.7849***	116.1479***	123.3177***	93.8232***
	[5.4045]	[6.4152]	[4.5895]	[4.1131]
Birds3	151.0088***	153.6631***	162.5631***	128.8402***
	[6.2833]	[6.7938]	[6.4157]	[5.2172]
Birds4	166.4515***	166.9389***	175.7203***	142.4483***
	[6.7937]	[7.6786]	[7.1016]	[5.7398]
Size	0.0300***	0.0273***	0.0309***	0.0800***
	[0.0040]	[0.0037]	[0.0035]	[0.0076]
SQ	-1.4423	-10.9016+	-5.9341	-11.4699+
	[6.5190]	[6.5192]	[4.8503]	[5.8906]
Price	-4.2391***	-4.2359***	-4.2866***	-4.1443***
	[0.0327]	[0.0338]	[0.0351]	[0.0378]
Woodland?	-1.51	-1.5119	-0.5719	0.2945
	[2.0169]	[2.4629]	[1.4786]	[1.8670]
Distance to competing sites		4.6588*	-8.4948+	9.4768**
		[2.1579]	[4.3784]	[3.6038]
Substitutes at site		0.1495	-1.0499	-1.0058
		[0.5234]	[1.3780]	[0.6300]
Substitutes at respondent		2.1435	-1.3331	4.7562***
		[3.2067]	[2.1831]	[1.2770]
Income	-0.0019	-0.0024+	-0.0013	-0.0005
	[0.0012]	[0.0012]	[0.0009]	[0.0013]
Frequent user?	0.9629	7.0366+	1.5142	-4.9492
	[6.0845]	[3.9180]	[4.1000]	[3.8900]
Higher education?	-3.2318	2.6921	-0.9424	-0.8519
	[4.6853]	[6.4378]	[3.0505]	[3.9082]
Maps?	-1.0708	5.8	2.4491	
	[8.5526]	[4.6599]	[4.0195]	

Note: All models were estimated with 50 Halton Draws, except for model 2, which was estimated with multiple numbers of Halton Draws (50, 300, 500, 1500 and 3,000) and also in preference space, without meaningful change of results for substitutes' metrics. Results reported for model 2 were generated with 3,000 Halton draws. "Substitutes at respondent", "Income", "Frequent user?", "Higher education?" contain interaction with SQ dummy. Standard errors in brackets. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

Table 5 Estimation results (cont.)

Variable	Model 0	Model 1	Model 2	Model 3
Maps vs substitutes at respondent			3.4696	
			[2.7162]	
Maps vs substitutes at site			1.2446	
			[1.4745]	
Maps vs distance to competing sites			14.4815**	
			[4.8400]	
Maps vs distance to site			4.9122	
			[3.7349]	
S.D.				
Access	51.8437***	44.7084***	55.4396***	35.5397***
	[4.4877]	[2.8457]	[2.9739]	[3.8070]
Birds1	36.1393***	14.0139***	57.5242***	17.2241***
	[4.6488]	[3.3075]	[3.8044]	[4.9242]
Birds2	37.8020***	-10.8111*	32.1670***	23.2426***
	[2.9727]	[5.0921]	[2.4673]	[2.9191]
Birds3	3.2981	0.5989	7.0806+	7.1865+
	[5.4745]	[6.4515]	[3.6746]	[4.2963]
Birds4	1.1636	0.3823	9.8624*	4.6164
	[2.3309]	[3.9250]	[4.0995]	[3.5087]
Price	0.0444	0.0271	-0.2775	0.0671
	[0.0695]	[0.1230]	[0.2327]	[0.0564]
Distance to site		10.1376***		2.565
		[1.9131]		[3.9858]
Distance to competing sites				1.2986
				[4.5561]
Size				0.0262*
				[0.0117]
Country				10.7170***
				[3.1843]
Respondents	2230	2230	2230	1903
Observations	107,040	107,040	107040	91,344
chi2	27250	25719	24583	20235
p	0	0	0	0
ll	- 27,683	- 27,619	-27438	- 23,336
AIC	55,408	55,282	54,925	46,719
BIC	27,736	27,674	27,501	23,395

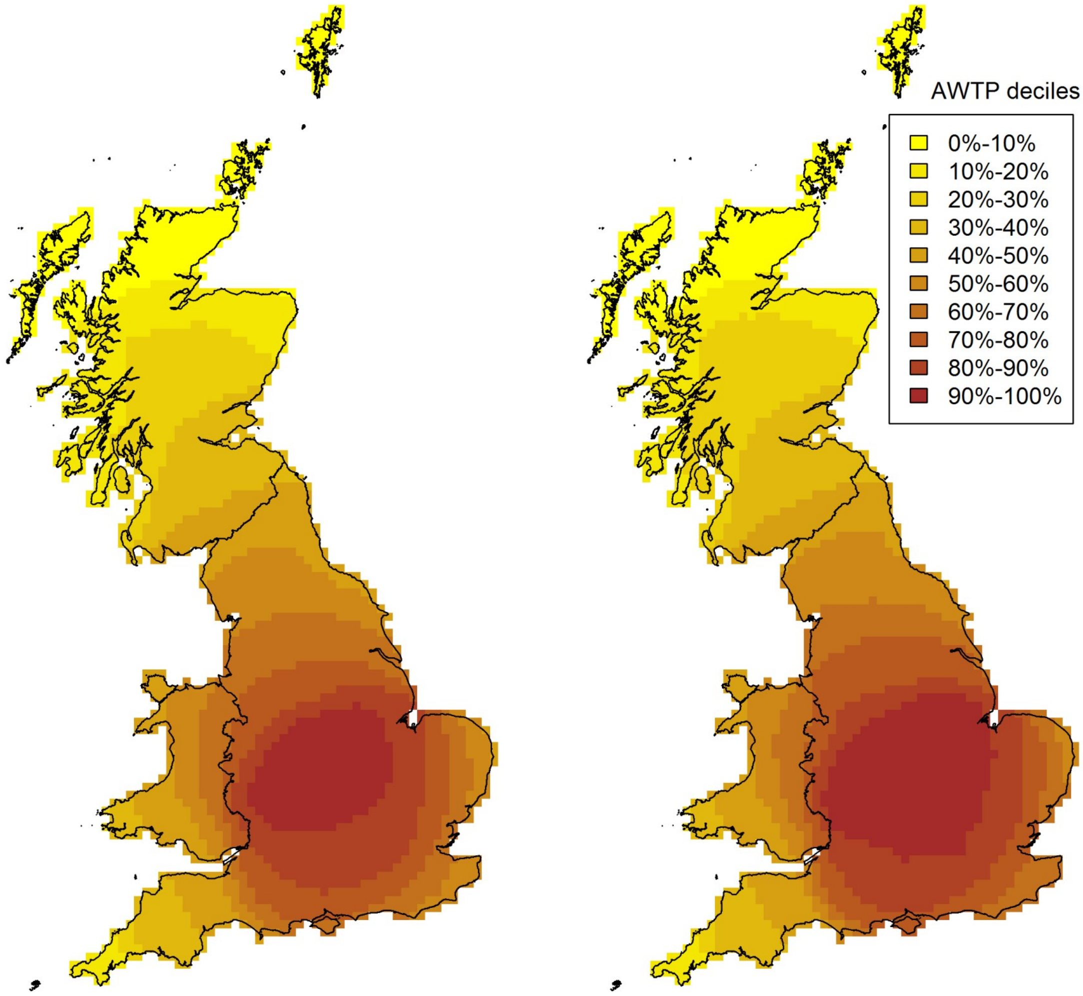
5.2 WTP map

The WTP map was based only on the subsample exposed to maps, which revealed more consistent results regarding substitute influence (therefore, estimates come from table 5, model 3; only the coefficient of explicit substitutes was used[8]). WTP with substitutes was, across all levels of biodiversity and sizes of converted site and for the average GB cell, 3% larger (for some cells it reached 6.5%), taking as baseline the model without substitutes (table 5, model 0). The difference was statistically significant at <0.01% and visible at naked eye throughout GB territory (figure 2).

However, if the effect of effective availability of convertible sites (arable land) is accounted for, the effect of substitutes increased to 30% in average and it is salient at naked eye (figure 3). This is due to a coefficient for the size attribute almost three times larger for the model with substitutes, attesting that accounting for substitutes also made considerable difference for the measurement of the effects of other attributes. This fact is less prominent based on actual convertible sizes because they are, at 10 km resolution, larger, on average, than the attribute levels (for instance, 100 ha, a number in between two DCE levels was used in figure 2, but average size of high-intensity agriculture was 1,881 ha in figure 3).

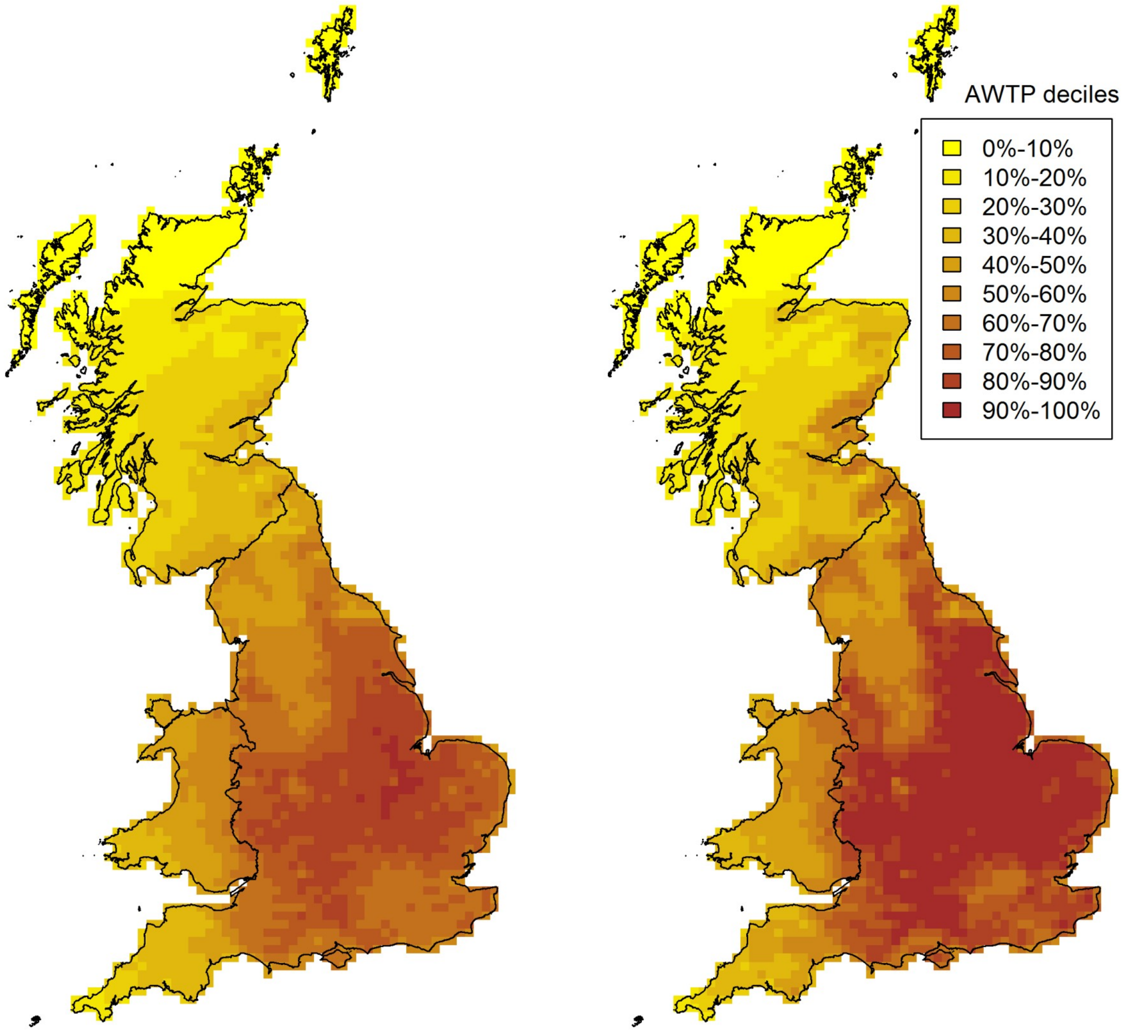
[8] This is coherent with the underlying mental exercise behind the WTP map, which consists in assuming that all cells of GB could give place to land use shift towards low intensity land use. Therefore, all sites already under low intensity agriculture are explicit substitutes in this exercise. Another option would be to also consider the coefficient of implicit substitutes (significant in model 3), but that would not only be incoherent with the explicit character of substitutes just pointed but would lead to double counting of substitutes' effect (as it meant accounting effect of substitutes when they are implicit and explicit).

Figure 2 National conservation value maps, baseline model without substitutes' effect (model 0, left) and model with substitutes' effect (model 3, right)



Note: birds and size attributes were assigned, respectively, with lowest level and 100 ha. The same colour thresholds were used in the two maps.

Figure 3 National conservation value maps, effective availability of arable land, baseline model without substitutes' effect (model 0, left) and model with substitutes' effect (model 3, right)



Note: birds attribute was assigned with its lowest level. The same colour thresholds were used in the two maps.

6 Discussion and conclusion

This paper presented a novel approach to measure willingness to pay for the ecological and recreational returns of reduced intensity of agriculture. In particular, the effect of substitute goods was accounted for both explicitly in the stated preference survey and implicitly in ad-hoc fashion as GIS-observable low intensity land uses. We found that presenting choices on a map improved respondents' understanding of absolute distance between their location and each site offered, and also of the relative distances within a given choice set. To put differently, explicit substitutes were better understood as such when presented in maps for respondents, compared with the traditional tabular format. In addition, it was observed that implicit researcher-defined substitutes had effect on choices only at the surroundings of respondents that were exposed to the map format of elicitation. Such results are in accordance with previous studies, as detailed in the next paragraphs.

We first consider the question of reference location for assessment of substitute availability. Schaafsma et al (2012 and 2013), in DCEs of water-related recreation, found the direction between respondent and offered sites, a proxy for substitute availability, to have significant influence on choice. A second important result was that the statistical significance reflected the effective availability of substitute recreation sites. The substitute availability metric used by the authors captured substitutes around respondents and around the sites simultaneously. Therefore, there is both agreement with the results here found for substitutes around respondents and disagreement in regards to substitutes around offered sites. The latter suggests that preferences behind choices analysed in this paper may not be capturing only recreation travel decision. This is expected, as preferences for biodiversity and landscape beauty should also matter for the land use changes here valued. The paper by Liekens et al. (2013), which also measured preferences for land use changes towards conservation, found a significant effect for substitutes at sites too. However, the metric was a binary variable indicating whether site was surrounded by conservation areas, what authors recognized as imprecise for capturing substitutes. Summing up, thus, previous papers found similar results with regards to substitutes' effect, except when measuring this effect around the sites valued. This difference may be due to the nature of sites focussed by previous studies, which differs from the high-intensity agriculture sites valued in our survey.

Second, we turn to the question of the effect of presentation format. Johnston et al. (2016) also found such aspect to affect choices in a DCE about riparian restoration. More precisely, authors measured the effect of informing respondents about their residential location in regional maps against maps where their location was not indicated, and found this effect statistically significant. As expected, the effect was evidenced only for the attribute whose valuation depended on availability of information on respondents' proximity. Similarly, in this paper, substitute land uses, an attribute whose appropriate valuation depends on information regarding proximity, had an influence on choices which was proven to be affected by the individualized map effect.

In addition, the significance of explicit substitutes echoes findings by Schaafsma and Brouwer (2013), in which nearly all parameters capturing effect of explicit substitutes (alternative-specific constants for eleven offered sites) were significant. Explicit substitutes were also significant and had the expected sign on the paper by Lizin et al. (2016), which used the same metric for explicit substitutes as this paper (distance to other alternatives in the choice set).

The alteration of mapped aggregate WTP when accounting for substitutes is in line with Schaafsma et al. (2012 and 2013), Jorgensen et al. (2013) and Liekens et al. (2013). Other relevant factors for the aggregate WTP results were, as expected, population density, which increased the value of agriculture de-intensification, site-population distance and availability of arable land.

In synthesis, our results suggest that the spatial representation of substitutes yielded more consistent stated preferences for identification of priority locations for ecological de-intensification of agriculture. This leads us to believe that making all substitutes explicit on maps is a better approach than the traditional tabular format. The latter format can only supply respondents with incomplete information on the spatial characteristics of alternatives offered (as proposed by Johnston et al., 2016). However, the explicit substitutes approach is limited by the cognitive capacity of respondents, as shown by Schaafsma and Brower (2013). Fortunately, the significance of implicit substitutes around respondents' residences, that was also found in this paper, suggests a more feasible avenue for future research, that of designing spatial DCEs to balance the explicit and explicit approaches to substitutes.

Future work should also account for different effects of substitutes on users and non-users. Also, results obtained should be compared with the cost of converting sites, adding the perspective of landholders to the analysis, what would allow to detect hotspots for reducing intensification of agriculture.

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Appendix A

A.1 General approach

The first step of the procedure for classifying land uses was to define thresholds for percentages of land uses that could reasonably stablish the dominant land use at each and every GB pixel. The second step was to apply the thresholds to the percentages of each cell, generating the map.

The data available comprised shares of the area of 2km cells occupied by arable, grassland, woodland, urban and coastline/water bodies. The classification approach consisted in classifying cells according with whether a land use share was above a given threshold or not (dominance). It is intuitive that, the higher the threshold, the lower probability of a cell to exceed it and, thus, the lower classification's coverage. Let it be understood as "fuzzy" the situation in which one cell exceeds the thresholds associated with more than one land use, i.e., the cell is dominated by more than one land use (what, of course, is only possible if the sum of at least two thresholds is below 100%). Again, the higher thresholds are, the less probable is that they are exceeded, the lower classification fuzzyness (number of cells with more than one dominant land use). There is, thus, a fuzzyness-coverage trade-off: decreasing all thresholds increases the number of cells with at least one dominant land use (more coverage) and increases the number of cells with more than one land use (more fuzzyness). If a trade-off exists, optimization is possible. There must be a combination of thresholds that provides the lowest fuzzyness/coverage ratio. This is equivalent to seek the threshold set that maximizes the number of cells with only one dominant land use[9], this being the criteria adopted.

A.2 First step

Twelve threshold sets were applied to data. For simplicity, the same threshold value was used for all five land uses, being it equal to 0.2, 0.25, 0.3,…, 0.75 ([0.2;0.75] with a bin of 0.05). Of course, the threshold sets thus obtained were a small sample of all possible sets[10]. Therefore, the threshold set being sought is a local and not a global optimum.

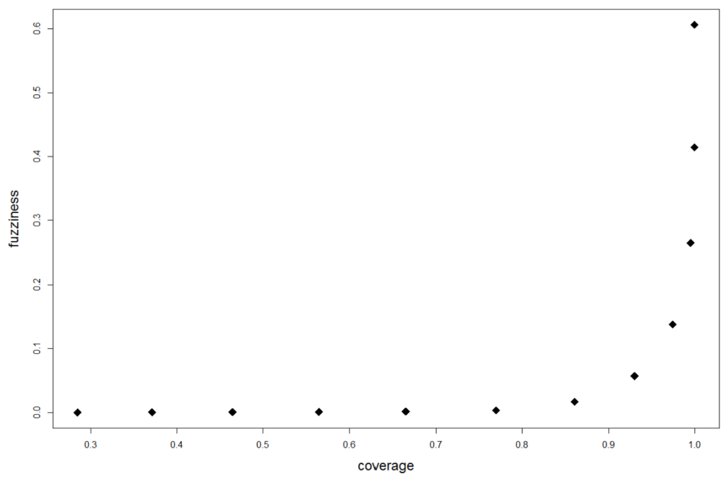
Figure A.1 shows the relationship between coverage and fuzziness. The latter was zero or negligible when the former was below 80%, but beyond that, a positive relation became clear. Figure A.2 shows the application of the optimization procedure to the data. For a threshold level of 40%, number of cells with only one dominant land use was maximized. Besides its simplicity, the "local best" criteria was capable of classifying 93% of cells, 87% with full certainty regarding dominant land use (assigned to only one class; appendix A). This seems a satisfactory level of "classification quality".

The detailed land use classification is found in table A.1, which show the count of cells classified in all 32 possible combinations of statuses regarding thresholds (there were 5 land uses, each classifiable in two status regarding thresholds).

[9] Also equal to maximize the number of cells that were classified but not in a fuzzy way.

[10] Only 12 sets were accounted for, but if thresholds of each land use were left free to differ, with 12 values for each, 248,832 would have to be considered.

Figure A.1 Trade-off between coverage (share of cells dominated by at least one land use; horizontal axis) and fuzziness (share of cells dominated by more than one land use; vertical axis)



Note: this plot was generated with threshold levels of 0.2, 0.25, 0.3,…, 0.75 for all three variables (same threshold level for the three variables).

Figure A.2 Threshold level (horizontal axis) and share of cells with only one dominant land use (vertical axis), maximum share and corresponding level highlighted by dashed lines

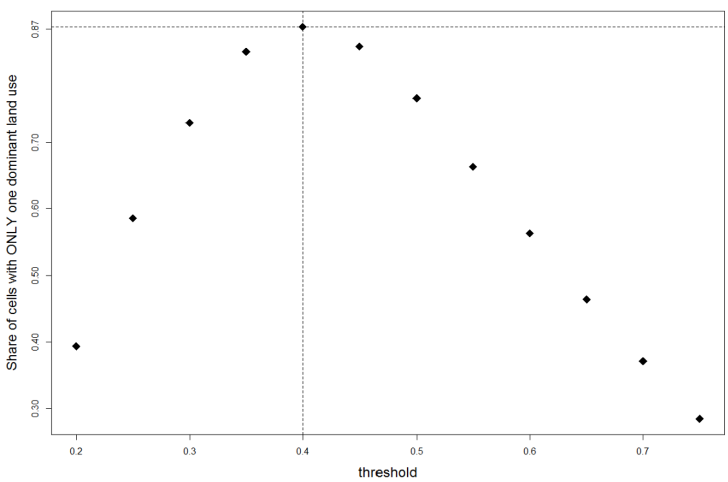


Table A.1 Detailed classification of GB cells according with the "local best" criteria (1 = 40% dominance threshold exceed, 0 = opposite case).

Woodland	Arable	Grassland	Urban	Water	Type	Count	%
0	0	0	0	0	0	3989	7%
1	0	0	0	0	1	3575	6%
0	1	0	0	0	1	12886	23%
0	0	1	0	0	1	27267	48%
0	0	0	1	0	1	4062	7%
0	0	0	0	1	1	2196	4%
1	1	0	0	0	2	47	0%
1	0	1	0	0	2	1161	2%
0	1	1	0	0	2	894	2%
1	0	0	1	0	2	23	0%
0	1	0	1	0	2	129	0%
0	0	1	1	0	2	121	0%
1	0	0	0	1	2	80	0%
0	1	0	0	1	2	30	0%
0	0	1	0	1	2	653	1%
0	0	0	1	1	2	112	0%
1	1	1	0	0	3	1	0%
1	1	0	1	0	3	0	0%
1	0	1	1	0	3	0	0%
0	1	1	1	0	3	0	0%
1	1	0	0	1	3	0	0%
1	0	1	0	1	3	4	0%
0	1	1	0	1	3	0	0%
1	0	0	1	1	3	0	0%
0	1	0	1	1	3	0	0%
0	0	1	1	1	3	0	0%
1	1	1	1	0	4	0	0%
1	1	1	0	1	4	0	0%
1	1	0	1	1	4	0	0%
1	0	1	1	1	4	0	0%
0	1	1	1	1	4	0	0%
1	1	1	1	1	5	0	0%
		Total				57230	100%