ORIGINAL ARTICLE

Spatial clustering of willingness to pay for ecosystem services

Valeria M. Toledo-Gallegos[1] | Jed Long[2] | Danny Campbell[1] |
Tobias Börger[3] | Nick Hanley[4]

[1]Applied Choice Research Group, University of Stirling, Management School, Stirling, UK

[2]Department of Geography, University of Western Ontario, London, ON, Canada

[3]Department of Business and Economics, Berlin School of Economics and Law, Berlin, Germany

[4]Institute of Biodiversity Animal Health and Comparative Medicine, University of Glasgow, Glasgow, UK

Correspondence
Valeria M. Toledo-Gallegos, Applied Choice Research Group, University of Stirling, Management School, Stirling, UK.
Email: valeria.toledo@stir.ac.uk

Abstract

Variations of willingness to pay (WTP) in geographical space have been characterised by the presence of localised patches of higher and lower values. However, to date, spatial valuation studies have not explored whether the distribution of hot (cold) spots of WTP is particular to each environmental good or if it follows similar patterns to other, comparable, environmental goods. We address this question by contrasting the spatial patterns of hot (cold) clusters of WTP for improvements in several ecosystem services. We geocoded individual-specific WTP estimates derived from a discrete choice experiment exploring preferences for ecosystem service improvements for three different catchment areas in Scotland comprising urban, agricultural, riverine and estuarine ecosystems. The local Moran's I statistic was used to find statistically significant local clusters and identify hot spots and cold spots. Finally, Multi-type Ripley's K and L functions were used to contrast the spatial patterns of local clusters of WTP among ecosystem services, and across case studies. Our results show that hotspots of WTP for environmental improvements tend to occur close to each other in space, regardless of the ecosystem service or the area under consideration. Our findings suggest that households sort themselves according to their preferences for estuarine ecosystem services.

1 | INTRODUCTION

The spatial variability of the ecosystem services (ES) supply is well documented in the ecological and geographical literature, and has been found to be dependent on the number, size, shape, connectivity or fragmentation of natural ecosystems (Haddad et al., 2015; Mitchell et al., 2013, 2015; Renó et al., 2016). Changes in the configuration of the spatial attributes of natural ecosystems impact their capacity to provide ES (Bastian et al., 2012; Turner et al., 2013). Currently, the capacity of estuaries to provide a broad range of ES to society is severely threatened by urban development, rural land management and pollution (Jacobs et al., 2013; O'Higgins et al., 2010).

With regard to the demand of ES, spatial valuation studies have found that environmental preferences are heterogeneously distributed in space for a variety of goods and services (Budziński et al., 2018; Schaafsma et al., 2013). Nonetheless, the role of the spatial dimensions in welfare analysis is often under-appreciated in the environmental valuation literature (De Valck & Rolfe, 2018; Glenk et al., 2020).

Some studies have analysed spatial autocorrelation (also called spatial dependence or unobserved spatial heterogeneity) between willingness to pay (WTP) estimates. However, to date, no research has estimated Ripley's K and L function with welfare estimates to explore whether the distribution of local clusters is particular to each environmental good or not. Therefore, the main objective of this paper is to examine whether the geographical distribution of significant hot or cold spots of WTP are similar among three different estuarine ES: (i) flood control (explained in terms of flood risk reduction); (ii) biodiversity; and (iii) recreation opportunities, when compared across three different estuarine catchment areas in Scotland, namely the Tay, the Forth and the Clyde. Contrasting the distribution of local clusters of WTP will allow us to understand whether there is a 'general formula' when developing locational targeting of environmental policies or not: that is, whether there is significant spatial overlap in the benefits produced by different environmental policies. Therefore, this study can help to develop better-informed policies since, for example, environmental managers would be able to better target environmental improvements if there is regulatory scope for flexibility in targeting of control measures for pollution, or woodland creation.

The rest of the paper is organised as follow: The following section reviews the relevant spatial valuation literature. Following that is a description of the study design, modelling framework and spatial analysis developed. The sample's descriptive statistics and the econometric estimates are presented and discussed in the fourth section. The final section concludes the paper and discusses the implications for policy and future research.

2 | SPATIAL PREFERENCE HETEROGENEITY

An increasing number of stated preference studies argue for a more explicit inclusion of the spatial dimension in the study of environmental preferences (see De Valck & Rolfe, 2018 and Glenk et al., 2020 for comprehensive reviews). Initially, efforts to characterise spatial

heterogeneity argued that 'global' patterns were causing WTP variations. Global patterns refer here to homogenous trends that apply within the limits of the area of analysis (i.e. distance decay, respondent's relative location to a geopolitical area) (Aregay et al., 2016; Bateman et al., 2006; Brouwer et al., 2010; Hanley et al., 2003; Johnston & Duke, 2009; Schaafsma et al., 2012). More recently, the assumption of global patterns of environmental preference has been challenged. Some authors suggest that environmental preferences are more likely to be explained by local associations that generate 'patchy' patterns (Johnston & Ramachandran, 2014; Johnston et al., 2011, 2015; Meyerhoff, 2013). Local spatial patterns are defined by the presence of 'non-continuous' or 'clustered' patterns of WTP variations across the area of analysis.

There are several reasons why we would expect that environmental preferences are characterised by local (i.e. discontinuous) rather than global (i.e. continuous) spatial patterns. First, spatial context is individual-specific, which means that people might develop a positive emotional connection or 'place attachment' to their local and familiar, or otherwise special context (Faccioli et al., 2018; Manzo, 2003, 2005). Second, individual WTP reflects the scarcity (or abundance) of the ES in their immediate environment (Bockstael, 1996; Johnston et al., 2002), as well as the local availability of and accessibility to substitutes (De Valck et al., 2017; Jørgensen et al., 2013). In this sense, the spatial pattern of preference heterogeneity might be partly explained by the underlying local distribution of the supply of ES. Thirdly, the cultural and socioeconomic characteristics which could impact society's WTP for environmental improvements also vary at the neighbourhood level. Therefore WTP patterns might follow the local spatial configuration of wealth, education levels, employment rates, cultural identity or environmental consciousness, which are reflected in the demand for ES (Brown et al., 2016; Faccioli et al., 2020; Perino et al., 2014). Finally, the existence of local patterns of WTP might reflect preference clusters that arise from residential sorting (Baerenklau et al., 2010; Klaiber & Phaneuf, 2010; Timmins & Murdock, 2007), which suggest that individuals chose their residence location according to their preferences for environmental goods (sometimes referred to as amenities in this context) and the costs of relocation.

Within the choice modelling framework, spatial preference heterogeneity has been studied in four main ways: (i) using spatially explicit choice attributes; (ii) including spatial covariates in the choice model; (iii) applying geographically weighted (lagged) choice models; and (iv) developing a second-stage spatial analysis with individual-specific WTP estimates. The first approach uses spatially explicit choice cards or attributes that may impose an additional cognitive burden on the respondent (Badura et al., 2019; Brouwer et al., 2010; Horne et al., 2005; Johnston et al., 2002; Logar & Brouwer, 2018; Meyerhoff et al., 2014; Schaafsma et al., 2012). The second approach might increase the risk of potential multicollinearity and model overspecification by estimating the interaction effects of spatial covariates, such as respondent's location, distance to the environmental good and substitutes, or other spatial environmental data (Abildtrup et al., 2013; Bergmann et al., 2008; De Valck et al., 2014; Meyerhoff, 2013; Schaafsma et al., 2013). A third approach suggested by Budziński et al. (2018) applies a geographically weighted model to analyse discrete choice data. Although this approach accounts for a non-linear relationship with respect to spatial dimensions, it also assumes global spatial autocorrelation of WTP estimates which is often found to be low or not statistically significant for environmental goods and services (Johnston & Ramachandran, 2014; Johnston et al., 2011, 2015; Meyerhoff, 2013; Vollmer et al., 2016).

The last approach is the one we use. The 'two-stage' approach of analysis is often used, as it allows the development of multiple types of analysis in the second step on individual-specific WTP estimates (i.e. conditional parameters) derived from a choice model estimated in the first step. For instance, it can assist in the visualisation of the geographical distribution of welfare estimates. Johnston et al. (2015) used inverse distance weighted interpolation to visualise the raw spatial patterns of the sampled points. Additionally, the second step can be used to study spatial effects on individual-specific WTP estimates. Vollmer et al. (2016) used a

non-parametric locally weighted scatterplot smoothing technique to contrast WTP estimates with the distance variable. Some studies have estimated panel random effects regressions on the second step which used distance (Campbell et al., 2008; Johnston & Ramachandran, 2014; Yao et al., 2014) and accessibility (Abildtrup et al., 2013) as explanatory variables. Similarly, Czajkowski et al. (2017) used geographical information system data related to forest characteristics to explain the variation in WTP estimates.

Environmental valuation studies have previously used individual-specific WTP estimates to assess spatial autocorrelation in the second stage of analysis. In contrast to Budziński et al. (2018) and Campbell et al. (2008), we test for both global and local spatial autocorrelation of welfare estimates using Moran's I statistics. Moreover, we extend previous analyses of hot spots and cold spots of WTP (Johnston & Ramachandran, 2014; Johnston et al., 2011, 2015; Meyerhoff, 2013) by developing a pair-wise analysis of spatial patterns in the second stage of analysis. To do so, we estimated two spatial summary statistics: the Multi-type Ripley K-cross function (Ripley, 1981) and L and Besag's (1977) transformation, known as the L-cross function.

Ripley's K and L functions have been previously used to generate policy recommendations in agri-environmental (Bamière et al., 2013), farming (Bamière et al., 2008), forestry (Li & Zhang, 2007) and pest management policy contexts (Lynch & Moorcroft, 2008). Although these functions have proved to be useful in understanding general spatial patterns that are relevant to consider when developing environmental policies, to our knowledge they have not been used before with environmental valuation data.

3 | METHODOLOGY

3.1 | Study design

We used data from a discrete choice experiment (DCE) distributed to members of a market research survey panel who lived in Scotland and were above 18 years old. A nation-wide web-based survey was administered in September 2016 (with a response rate of 72%) and aimed to explore the preferences of the Scottish general public for policies managing three estuarine ES: flood control, biodiversity and recreation opportunities. The improvements on the provision of ES were proposed to be delivered with a 'restoration project' operating
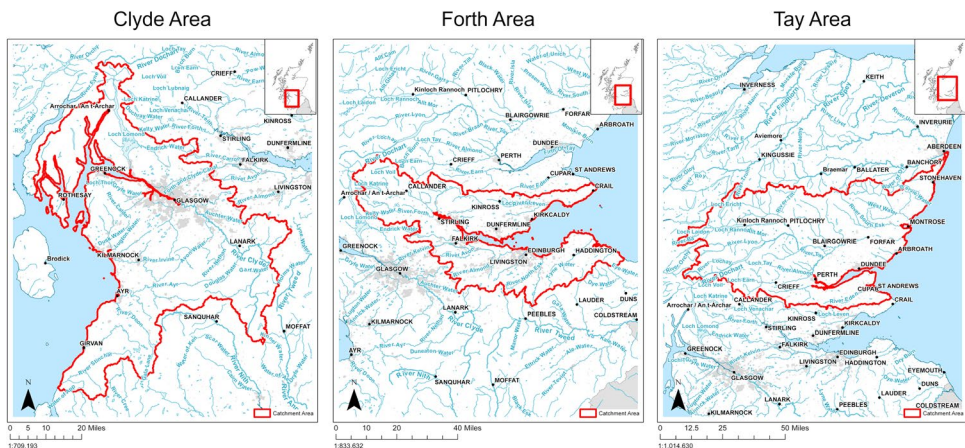

FIGURE 1 Catchment areas studied [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 1 Attribute levels used in the DCE

Attributes	Levels	Label[a]
Flood control	Increase in flood risk	–
	A slight reduction in flood risk	F1
	A large reduction in flood risk	F2
Biodiversity	Decrease in biodiversity	–
	A slight increase in biodiversity	B1
	A large increase in biodiversity	B2
Recreation	Decrease in recreation	–
	A slight increase in recreation	R1
	A large increase in recreation	R2
Cost of the policy (per year)	£5, £10, £20, £50, £75, £100	

[a]Dummy variable coding.

throughout the catchment areas of the river Clyde, Forth or Tay estuary in Scotland (see Figure 1). The objective of the restoration project is to improve the environmental quality of agricultural, riverine and estuarine ecosystems. Respondents were told that this restoration policy would be funded through an annual increase in the council tax (local tax) lasting 10 years.

We generated three versions of the survey, one for each study area. All versions of the questionnaire contained four main sections. The first section introduced the ES to be valued and the restoration project to be undertaken. The second section collected information on respondents' perceptions and knowledge of the ES in question. The third section included the DCE, as well as some debriefing and consistency questions. Finally, we collected the respondents' socioeconomic characteristics.

The attributes and levels (see Table 1) selection was based on expert consultation, a literature review and one-on-one surveys. The attribute labels and their corresponding descriptions were presented to respondents in a textual and visual format to convey the information in different ways (see Table A1 in Appendix S1).

Figure 2 presents an example of a choice card. In each choice card respondents were presented with three catchment management alternatives and were asked to choose their most preferred option. The first option depicts 'no new policy' scenario that would result in a prolongation of the current trend of degradation and decline of ES over time (UK National Ecosystem Assessment, 2011). The second and third options vary, but represent the development of a restoration project leading to improvements of the provision levels of at least one ES, and therefore are associated with positive costs to the respondent.

The survey was piloted on a sample of 61 individuals to obtain initial estimates (priors) and pre-test the choice context and experimental design. The three versions of the survey were randomly assigned to respondents, meaning that individuals could be answering the questionnaire with respect to the area they live in, or concerning a different catchment. Site-specific attribute coefficients were used as priors to generate three D-efficient designs of 18 choice cards in Ngene software (ChoiceMetrics, 2012). The experimental design used in this study aims to account for the site-specific environmental preferences. Thus, instead of blocking the experimental designs per case study, we merged all three site-specific designs into a pooled-design of 54 unlabelled choice cards. In the final design, all the cards were randomly grouped into unique sets (or blocks) of six choice cards, which were afterwards presented to the survey participants.
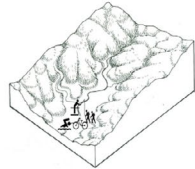
	Option 1 **(NO new policy)**	**Option 2**	**Option 3**
Flood control	Increase in flood risk	Slight reduction in flood risk	Increase in flood risk
Biodiversity	Decrease in biodiversity	Large increase in biodiversity	Slight increase in biodiversity
Recreation	Decrease in recreation	Large increase in recreation	Slight increase in recreation
Annual cost:	**£0**	**£100**	**£5**
Choice:	⬤	⬤	⬤

FIGURE 2 Choice card example [Colour figure can be viewed at wileyonlinelibrary.com]

3.2 | Choice modelling

According to the random utility maximisation theory (McFadden, 1973), the total utility that an individual derives from alternative i is the sum of its deterministic and random part. Following Train (2009), the utility of an alternative i for respondent n is given by:

$$U_{\text{int}} = V_{\text{int}} + \varepsilon_{\text{int}} = \beta'_n X_{\text{int}} + \varepsilon_{\text{int}} \tag{1}$$

where β_{int} is an individual set of parameters assumed from known distributions which depend on some unknown parameters θ to be estimated, and the error term ε_{int} which is independently and identically distributed according to a Gumbel distribution. We reparameterized Equation (1) to allow for the estimation of WTP distributions:

$$U_{\text{int}} = -\beta^{\text{cost}} \left(-\frac{\beta_{\text{n}}^{\text{non}-\text{cost}'}}{\beta^{\text{cost}}} X_{\text{int}}^{\text{non}-\text{cost}} - c_{\text{int}} \right) + \varepsilon_{\text{int}} = -\beta^{\text{cost}} \left(\alpha'_{\text{n}} X_{\text{int}}^{\text{non}-\text{cost}} - c_{\text{int}} \right) + \varepsilon_{\text{int}} \tag{2}$$

where β^{cost} is the parameter associated with price attribute, $\boldsymbol{\beta_n^{non-cost}}$ is a vector of parameters for the non-monetary attributes, $\mathbf{X_{int}^{non-cost}}$ is a vector containing the non-monetary attribute levels, and c_{int} is the cost of alternative i in choice situation t for respondent n. Finally, ε_{int} is the error term and $\boldsymbol{\alpha_n}$ is a vector of WTP estimates for each non-monetary attribute. The reparameterized model is a mixed logit model (MXL) in WTP-space in which the distribution of the vector $(\boldsymbol{\alpha_n}, \beta^{cost})$ are assumed, and the associated parameters are estimated (Train & Weeks, 2005), but β^{cost} is now confounded with the scale parameter.

In our model, we include an alternative specific constant (ASC) for the opt-out alternative and assume that all attribute parameters other than the cost parameter are normally distributed. The fixed cost assumption was used to avoid problems of lack of convergence that is common when all coefficients are specified as random (Revelt & Train, 1998) and because the long right tail of the lognormal distribution can cause unrealistic WTP estimates (Sillano & de Dios Ortúzar, 2005).[1] We note that using a WTP space representation of utility is immaterial when using a fixed cost, but we favour the direct estimation of the WTP distributions. In this case, the likelihood of the observed sequence of n th respondent's choices is given by:

$$L\left(y_n | X_n, \theta\right) = \int_{\boldsymbol{\alpha_n}} \prod_{t=1}^{Tn} \sum_{i=1}^{I} y_{int} \frac{e^{V_{int}}}{\sum_{j=1}^{J} e^{V_{ijt}}} f\left(\boldsymbol{\alpha_n} | \theta\right) d\boldsymbol{\alpha_n} \tag{3}$$

The likelihood function is integrated over the random effects. This expression cannot be solved analytically and is thus approximated with simulation-based estimation (1,000 Sobol draws).[2] In order to test the spatial correlation of the WTP estimates, we calculate the conditional estimates (or individual-specific WTP). This was done by using Bayes' Theorem as follows (Train, 2009):

$$\widehat{\boldsymbol{\alpha_n}} = \int \boldsymbol{\alpha_n} \frac{p\left(y_n | X_n, \theta, \boldsymbol{\alpha_n}, \beta^{cost}\right) f\left(\boldsymbol{\alpha_n} | \theta\right)}{p\left(y_n | X_n, \theta\right)} d\left(\boldsymbol{\alpha_n}\right) \tag{4}$$

The MXL model was applied to the pooled choice dataset, as well as to each site-specific dataset. All models were coded and estimated in R software version 3.3.2 (R Core Team, 2020) using the *Apollo* package (Hess & Palma, 2019). As we used three ES attributes with two improved levels, we obtained six conditional WTP estimates per respondent and for each MXL model.

3.3 | Cluster analysis of willingness to pay for ES

In the context of the environmental valuation body of literature, the analysis of local clustering allows the measurement of different concepts of spatial association between WTP estimates, such as the spatial clustering of similar or dissimilar values (Anselin, 1995). We used the

---

[1]We estimated the pooled and non-pooled models (i.e. All, Clyde, Forth and Tay) in preference space using a lognormal cost. Although these models fit the choice data better, they lead to unrealistically high (figures of thousand pounds) unconditional and conditional WTP estimates (mean and median) for all attributes. Additionally, we estimated the same models in WTP space and found that at least one model presented convergence issues. Since we required all the model outputs to compute the spatial statistics, we could not use this modelling approach.

[2]Czajkowski and Budzinksi (2017) suggest to use a minimum of 1,000 Sobol draws for having ≤ 5% probability that parameter estimates differ by ≥ 5% from true values.

postcode coordinates[3] (centroid) to geocode the data and the individual-specific mean WTP of all datasets to test for the presence of spatial autocorrelation. The conditional mean estimate was chosen as it is the most likely WTP value for each respondent to occur (conditioned on their observed responses or choices).

We first calculated global measures of autocorrelation, as it has been suggested that the presence of significant global spatial autocorrelation could increase the probability of incorrectly identifying local spatial autocorrelation (Ord & Getis, 2001). This was done using Moran's I statistic (Moran, 1950) defined as:

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} \omega_{ij}(WTP_i - \overline{WTP})(WTP_j - \overline{WTP})}{\sum_{i=1}^{n} \sum_{j=1}^{n} \omega_{ij} \sum_{j=1}^{i=n} (WTP_i - \overline{WTP})^2}, i \neq j \tag{5}$$

where n is the number of spatial units indexed by i and j, and ω_{ij} is the spatial weight between observation i and j.

Let the centroid distances from each spatial unit i to all units $j \neq i$ be ranked as follows: $d_{ij(1)} \leq d_{ij(2)} \leq d_{ij(n-1)}$. Then for each $k = 1, ..., n - 1$, the set $N_k(i) = \{j(1), j(2), ..., j(k)\}$ contains the k closest units to i. For each given k, the k-nearest neighbour weight matrix (W) then has spatial weights defined as follows:

$$\omega_{ij} = \begin{cases} 1, & j \in N_k(i) \\ 0, & \text{otherwise} \end{cases}, \tag{6}$$

The underlying assumption of the global Moran's I test is that the spatial process promoting the observed estimates of WTP is a random chance. Rejecting the null hypothesis would suggest the existence of spatial autocorrelation of WTP estimates. The value of Moran's I ranges between +1 and −1, with positive values indicating that WTP estimates are globally clustered (or positive autocorrelation) and negative values indicating they are globally dispersed (or negative autocorrelation). Values of $I \sim 0$ indicate that WTP estimates are distributed randomly in space.

Since Moran's I statistic consists of the summation of individual cross products, the local indicator of spatial autocorrelation (LISA) can be used to evaluate clustering in each spatial unit and to evaluate the statistical significance for each local Moran's I_i index. In other words, the LISA statistics are used to test if spatial autocorrelation is more likely to occur within subsets of datasets (Anselin, 1995).

We applied the local Moran's I_i defined by Getis (2010) as:

$$I_i = \frac{WTP_i - \overline{WTP}}{\left((1/n) \sum_{j=1}^{i=n} (WTP_i - \overline{WTP})^2\right)} \sum_{j=1}^{n} \omega_{ij}(WTP_i - WTP_j), i \neq j \tag{7}$$

The local Moran's I_i values for the pooled and the site-specific datasets were classified into five categories that distinguish between insignificant clusters, as well as four types of significant clusters. The first two types of significant clusters are hotspots (High-High or HH) and coldspots (Low-Low or LL). The former represents respondents with high values having neighbours with high values, whereas the latter refers to respondents with low values surrounded by neighbours with low values. The remaining two categories are respondents with high values

---

[3]The postcode unit represents a relatively precise measure of a respondent's residential location since each postcode in the UK covers an average of only 15 properties (Ordnance Survey, 2018).

which have neighbours with low values (High-Low or HL) and respondents with low values which have neighbours with high values (Low-High or LH).

In contrast to Campbell et al. (2008, 2009) who developed a spatial autocorrelation analysis in a polygon format (averaging administrative areas), we used a point analysis and accounted for the irregular distribution of the sample in space by using a k-nearest neighbour weight matrix definition to estimate the local Moran's I_i. This was done for several reasons. First, as we used an online panel dataset to target the surveys to a representative and not homogenously distributed sample in space, to average this data would result in imbalanced or biased estimates. Second, it has been suggested that averaging counties or states can influence the strength of measured spatial autocorrelation (Meyerhoff, 2013; Openshaw, 1983). Finally and most importantly, averaging data points inside an administrative area imposes a linear pattern in its geographical limits and might obscure the presence of 'patchy' patterns of marginal WTP for ES improvements in Scotland.

The *spedep* package in R (Bivand & Piras, 2015) was used to estimate the spatial weights matrix, as well as to conduct both global and local measures of spatial autocorrelation.

3.4 | Summary functions for comparing spatial point patterns

The significant local clusters identified in the analysis of the three site-specific datasets were used to proceed with the comparison of the spatial patterns among estuarine ES, and across the three catchment areas. We used a multi-type point pattern for HH and LL individuals treated as a single pattern of n points and marked them by the specific estuary (three types) and the ES they refer to (three types). It is assumed that the point process X extends throughout a 2-D space, but is only observed inside the region W, that is, the sampling window. Our data consist of an unordered set $x = \{x_1, \ldots x_n\}$, $x_i \in W$, $n \geq 0$ of points x_i in W. A marked point pattern is explained as an unordered set $y = \{(x_1, m_1), \ldots (x_n, m_n)\}$, $x_i \in W, m_i \in M$, where x_i are the locations, m_i are the marks which allow grouping the points into types, W is the sampling window, and M is the space of possible marks.

The Multi-type Ripley's K function (cross-type) was used to test whether or not there is clustering between all pairs of types (Ripley, 1981). Let X_j denote the sub-patterns of points (multi-type point process) type j, with intensity (density of points) λ_j, which is the average number of points per unit area in a point pattern dataset. It is assumed that the point process X is homogenous (i.e. intensity is constant) for any subregion B of a 2-D space. Thus, the expected number of points in B is proportional to the area of B: $E[N(X \cap B)] = \lambda \text{area}(B)$, and the constant of proportionality is the intensity. In a homogenous point process the empirical density of points is an unbiased estimator of the true intensity λ and is estimated as follows:

$$\bar{\lambda} = \text{n}(x) / \text{area}(W) \quad (8)$$

Then the bivariate K function for any pair of types i and j. is as follows:

$$K_{ij}(r) = 1/\lambda_j E \quad (9)$$

where E is the expected number of points of type j within a distance r of a typical point of type i in the process X_i. The *spatstat* package in R was used to compute the estimator K_{ij} of the Ripley K-cross function. It assumes that X is a realisation of a stationary (spatially homogeneous) random spatial pointrocess in the plane which is typically modelled as a Poisson point process, observed through a bounded window (Baddeley et al., 2015).

For graphing purposes, we used a variance stabilising transformation of the K-cross function that derives into the L-cross function defined by Besag (1977) as:

$$L_{ij}(r) = \sqrt{\frac{K_{ij}(r)}{\pi}} \tag{10}$$

Both summary functions K_{ij} and L_{ij} are called 'cross-type', 'bivariate' or 'i-to-j' when $i \neq j$. If X_i and X_j point processes are probabilistically independent then $K_{ij}(r) = \pi r^2$ and $L_{ij}(r) = r$, regardless of the pattern of either type of point (Ripley, 1981). Estimating these spatial summary statistics allows comparing the observed pattern of HH (or LL) to a Complete Spatial Randomness and Independence (CSRI) process. Plotting r versus $L_{ij}(r)$ provides a convenient reference line at zero. Values of $L_{ij}(r) < r$ indicate inhibition between two types of points, whereas values of $L_{ij}(r) > r$ indicate more clustering than expected under CSRI.

Following Ripley (1977), we extended the exploratory analysis of HH (or LL) point pattern to include a Monte Carlo test of goodness-of-fit to the homogeneous Poisson process. The L_{ij} function was plotted together with a simulation of envelopes (1,000 simulations), where each simulation is generated by the homogeneous Poisson point process with intensities estimated from the data (i.e. HH or LL). The envelopes serve as the critical limits for a Monte Carlo test of the null hypothesis of a random Poisson point process. If the observed L-cross function is outside the simulation envelope, it shows clustering between X_i and X_j. Clustering between a pair of types of points occurs when the events of each type are closer to each other than expected under the assumption that the two processes are independent.

4 | RESULTS AND DISCUSSION

Table 2 summarises household sample and subsample statistics. After deleting protest bid individuals (2%),[4] as well as deleting individuals without postcode (1%) and income information (3%), we obtained a final sample of 571 individuals. Each individual answered six choice cards, meaning that we obtained 3,426 choice observations (approximately a third for each estuary). *T*-tests showed that this sample is representative of the Scottish population in most of the available statistics, except age.[5]

4.1 | Regression results and welfare estimates

Table 3 presents the results of the MXL model estimated in WTP space using the (i) pooled dataset, as well as the site-specific choices for the (ii) Clyde, (iii) Forth and (iv) Tay estuaries. After testing for several specifications, the utility was defined as a linear function of dummy coded attributes, the ASC alone and in interaction with respondent's socioeconomic characteristics.

The four MXL models applied to the choices for environmental improvements in estuarine ES have relatively high explanatory power (rho squared between 0.28 to 0.29).[6] Instead of presenting the attribute preference coefficients, Table 3 shows the estimates of marginal prices WTP (mean and standard deviation) derived directly from the estimations in *WTP space*. We found positive and significant mean WTP for all improvements in estuarine ES.

---

[4]We used follow-up questions to differentiate between protest and true zero responses. Protest respondents were removed from the analysis and were identified as those who consistently chose the 'status quo' alternative and selected the following statements: (i) I believe I should not be the one paying for it; (ii) I don't believe that my payment will be used effectively; and (iii) I don't pay taxes and/or I would prefer another mechanism for paying.

[5]The percentage of respondents being above 64 years old is significantly different, with 19.69% obtained in our sample versus 16.81% for Scotland reported in the UK census (Office for National Statistics, 2011).

[6]Louviere et al. (2000) suggest that rho-squared values between 0.2 and 0.4 indicate a good model fit.

TABLE 2 Sample summary statistics of respondents and their households

Variables	All sites pooled (N = 571)	Tay questionnaire (n = 189)	Clyde questionnaire (n = 188)	Forth questionnaire (n = 194)
Income (£ per month)	1820.76 (1127.51)	1925.31 (1170.21)	1847.97 (1169.30)	1692.53 (1028.11)
Age	50.23 (16.25)	49.24 (16.19)	48.85 (16.46)	52.54 (15.87)
Household size	2.34 (1.26)	2.55 (1.43)	2.33 (1.25)	2.14 (1.03)
Gender (% female)	53.77	57.14	53.19	51.03
Education (% with university degree and above)	40.46	43.92	36.70	40.72
Employment (% economically active)	61.12	66.67	63.30	53.61
Residency in the area (% residents)	31.70	14.29	44.68	36.08
Visited the area for outdoor recreational activities (% visitors)	53.24	49.74	52.13	57.73
People perceiving a better environmental status in the area (% respondents)	18.56	16.93	21.81	17.01
People perceiving a worse environmental status in the area (% respondents)	19.61	22.75	15.96	20.10

Note: Given are means and standard deviations (in parentheses).

The standard deviations reveal significant unobserved heterogeneity across all attribute levels, except for slight improvements in biodiversity (B1) and recreation (R1). The majority of the attribute coefficients show positive scope effects, which suggest that respondents have a stronger preference for options providing more substantial improvements in the provision levels of ES. In other regards, we found that the ASC does not always exhibit a negative sign, but in these cases, it fails to reach significance. The presence of a negative ASC suggests that on average respondents' utility is impacted positively when moving away from the *status quo*.

As expected, the results regarding the user-specific ASC vary depending on the dataset analysed. However, it can be seen that for most of the cases, the sign remains constant across datasets and that the significance of the coefficients is commonly reached for the larger sample (pooled dataset). Similarly to previous research (Birol et al., 2009; Börger & Hattam, 2017; Botzen et al., 2012), we found that for the pooled dataset the ASC of visitors, female and older people is negative and significant (at least at the 10% level). This result indicates their preference for moving away from the *status quo* and to develop the project delivering improvements in ES.

Table 4 displays a summary of the individual-specific WTP estimates for all estuarine ES improvements which were calculated using both the pooled and site-specific datasets. These conditional estimates can be interpreted as the mean, minimum and maximum value of the parameters of the subpopulation that would have made the same choices while facing the same choice situation. It can be noted that the higher WTP estimates are commonly associated with

TABLE 3 MXL estimates for ES improvement in WTP space

Attribute	All		Clyde		Forth		Tay	
	Coeff. (Mean)	Coeff. (SD)	Coeff. (Mean)	Coeff. (SD)	Coeff. (Mean)	Coeff. (SD)	Coeff. (Mean)	Coeff. (SD)
F1	111.30***	42.74***	100.16***	34.82**	114.56***	49.99***	118.99***	44.65*
	(6.84)	(8.76)	(9.61)	(12.94)	(12.86)	(14.65)	(13.62)	(18.02)
F2	141.30***	78.66***	125.74***	69.71***	129.21***	88.08***	170.70***	70.61***
	(8.48)	(8.45)	(12.03)	(11.86)	(15.03)	(16.66)	(17.90)	(16.51)
B1	114.00***	0.69	105.45***	1.75	113.65***	41.30**	117.45***	0.80
	(7.08)	(21.22)	(10.51)	(31.77)	(13.24)	(15.70)	(13.59)	(21.92)
B2	122.11***	54.68***	94.89***	37.33*	128.71***	58.94***	146.17***	63.97***
	(7.72)	(7.80)	(10.46)	(12.07)	(14.42)	(15.06)	(16.26)	(15.09)
R1	42.21***	2.80	38.78***	0.27	51.63***	1.45	36.91***	6.62
	(5.04)	(14.04)	(7.40)	(21.63)	(9.54)	(17.21)	(9.68)	(44.25)
R2	42.60***	42.59***	41.89***	38.18**	38.50***	54.72***	48.54***	15.39
	(5.34)	(7.98)	(8.24)	(12.71)	(9.91)	(13.59)	(9.66)	(66.02)
Cost	−0.01***		−0.01***		−0.01***		−0.01***	
	(0.00)		(0.00)		(0.00)		(0.00)	
ASC	−0.08	3.11***	0.81	3.40***	0.55	3.03***	−1.70*	2.67***
	(0.52)	(0.25)	(0.93)	(0.49)	(0.94)	(0.45)	(0.93)	(0.42)
ASC × resident	0.39	–	0.38	–	0.25	–	−0.50	–
	(0.43)	–	(0.85)	–	(0.73)	–	(0.99)	–
ASC × visitor	−1.05**	–	−0.84	–	−1.51*	–	−1.10	–
	(0.41)	–	(0.84)	–	(0.75)	–	(0.63)	–
ASC × female	−0.73*	–	−0.67	–	−1.08	–	−0.01	–
	(0.38)	–	(0.70)	–	(0.66)	–	(0.67)	–
ASC × age	−1.05**	–	−1.51[+]	–	−1.43*	–	−0.22	–
	(0.38)	–	(0.75)	–	(0.64)	–	(0.64)	–
ASC × graduate	0.21	–	0.42	–	−0.73	–	0.99	–
	(0.38)	–	(0.74)	–	(0.71)	–	(0.63)	–
ASC × income	−0.03[+]	–	−0.06*	–	0.01	–	0.00	–
	(0.01)	–	(0.03)	–	(0.03)	–	(0.02)	–
Log-likelihood	−2662.65		−870.54		−903.17		−864.69	
Observations	3426.00		1128.00		1164.00		1134.00	
Adjusted rho-sq	0.29		0.28		0.28		0.29	
AIC	5367.29		1783.09		1848.34		1771.39	
BIC	5496.21		1888.68		1954.59		1877.09	

Note: Two-tailed *t*-test indicates values approaching close to significance (+) and with 10% (*), 5% (**) and 1% (***) significance levels.

Standard errors are reported in parentheses and computed by Delta method.

flood control, but are followed closely by the welfare estimates for biodiversity improvements. Recreational changes in the catchment area are smaller by at least a factor of two than the former and latter. These findings are in line with a previous study valuing comparable ES wetlands (in Poland) as the ranking of ES by marginal WTP is consistent with that observed in Birol et al. (2009).

TABLE 4 Individual-specific WTP estimates for ES improvements, Unit GBP/year

Attribute	All		Clyde		Forth		Tay	
	Mean	Min/Max	Mean	Min/Max	Mean	Min/Max	Mean	Min/Max
F1	111.30	62.70/157.80	100.20	68.57/130.80	114.30	51.59/161.00	119.00	69.69/166.60
F2	141.30	12.45/246.20	125.90	10.17/221.90	129.20	1.75/254.60	170.40	91.45/251.60
B1	114.00	113.80/114.20	105.50	105.20/105.70	113.70	67.95/152.60	117.50	117.40/117.90
B2	122.00	54.97/204.10	95.03	55.83/149.00	128.90	62.31/204.60	146.10	51.58/228.10
R1	42.20	41.38/42.60	38.78	38.72/38.83	51.63	51.23/51.99	36.90	33.19/38.62
R2	42.65	−10.35/100.90	41.96	−1.29/94.12	38.76	−33.9/121.50	48.51	42.19/55.68
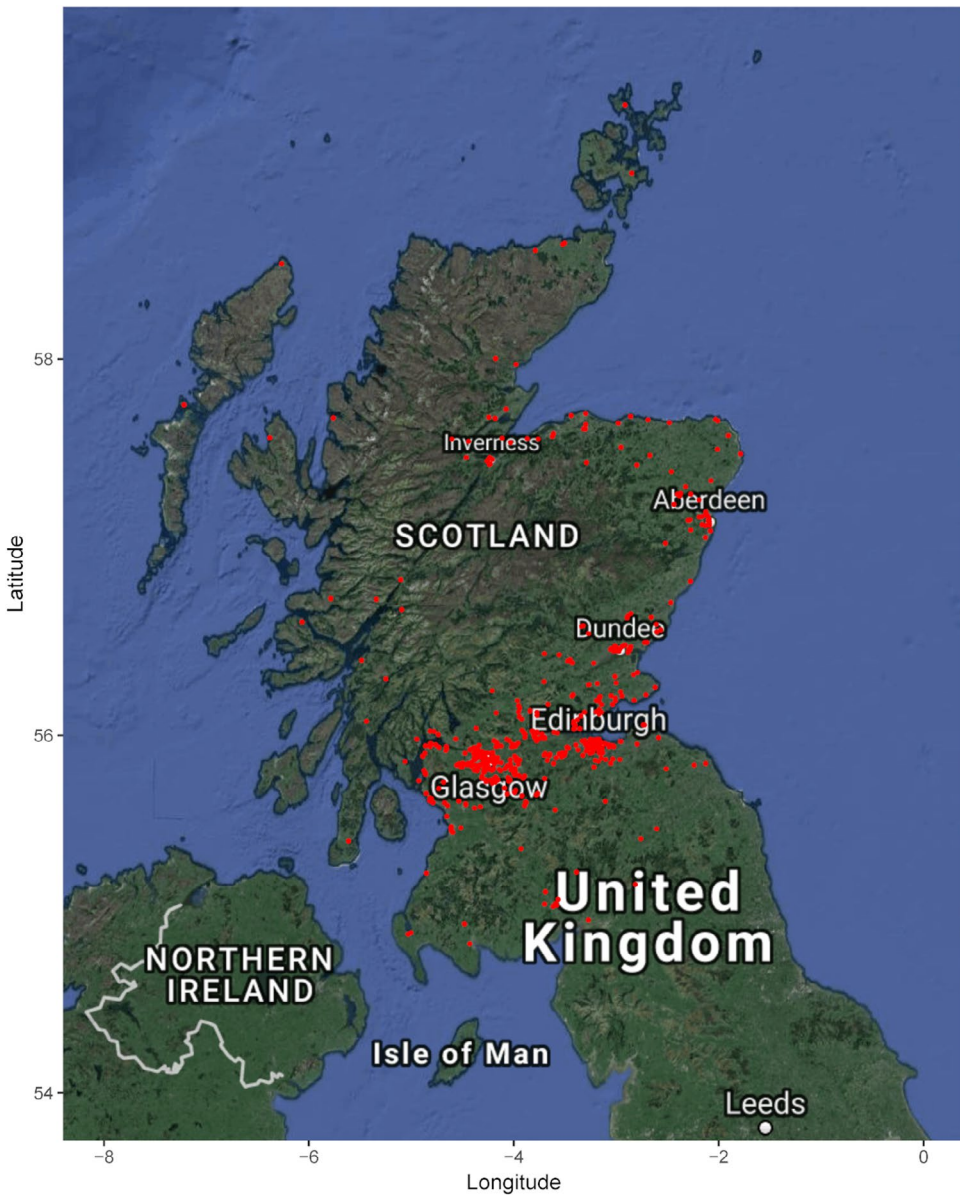
FIGURE 3   Geographical distribution of WTP sample points in Scotland (source: Google, n.d.) [Colour figure can be viewed at wileyonlinelibrary.com]

Results also reveal that higher disparities in WTP estimates (max-min) are found for the large flood control improvements (F2), whereas the substantially smaller distribution of WTP estimates relates to slight enhancements in biodiversity and recreational services (B1 and R1).

4.2 | Spatial autocorrelation of willingness to pay for ES

Figure 3 shows that the spatial point distribution of the sample used in this analysis is higher in the Central Belt of Scotland and the Aberdeen region, which are the most densely populated

TABLE 5 Number of local clusters of WTP estimates for ES improvements

Attribute	HH				LL				HL				LH				NS			
	All	Clyde	Forth	Tay	All	Clyde	Forth	Tay	All	Clyde	Forth	Tay	All	Clyde	Forth	Tay	All	Clyde	Forth	Tay
F1	24	5	2	4	26	1	5	3	0	0	0	0	0	0	0	0	521	182	187	182
	(4)	(3)	(1)	(2)	(5)	(1)	(3)	(2)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(91)	(97)	(96)	(96)
F2	13	9	3	1	17	3	11	0	0	0	0	0	0	0	0	0	541	176	180	188
	(2)	(5)	(2)	(1)	(3)	(2)	(6)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(95)	(94)	(93)	(99)
B1	7	2	4	2	10	1	11	0	0	0	0	0	0	0	0	0	554	185	179	187
	(1)	(1)	(2)	(1)	(2)	(1)	(6)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(97)	(98)	(92)	(99)
B2	10	4	11	3	7	1	6	10	0	0	0	0	0	0	0	0	554	183	177	176
	(2)	(2)	(6)	(2)	(1)	(1)	(3)	(5)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(97)	(97)	(91)	(93)
R1	7	6	2	6	6	1	1	2	0	0	0	0	0	0	0	0	558	181	191	181
	(1)	(3)	(1)	(3)	(1)	(1)	(1)	(1)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(98)	(96)	(98)	(96)
R2	13	0	7	6	14	2	8	2	0	0	0	0	0	0	0	0	544	186	179	181
	(2)	(0)	(4)	(3)	(2)	(1)	(4)	(1)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(95)	(99)	(92)	(96)

Abbreviations: HH, high-high; HL, low-high; LH, high-low; LL, low-low; NS, not significant; using k, 23 for neighbourhood definition.

The sum of the number of clusters associated with the same dataset (e.g. "All") per row leads to the total sample (n = 571).

Percentages are indicated in parenthesis and are calculated by multiplying the value by 100 to be then divided by the total sample (571, 189,188 and 194, respectively).

areas of Scotland. The geocoded individual-specific mean WTP data points obtained from the pooled and site-specific choice models were used to explore for spatial autocorrelation.

We first tested for global spatial correlation using Moran's I statistic. Results are shown in Table B.1 in Appendix S2, online, and only indicate the presence of globally clustered WTP mean values for delivering slight improvements in flood control when analysing the pooled dataset. Although not conclusive, the findings show that for the whole study area (i.e. Scotland), individuals living close together have similar demand for large improvements in flood reduction. This 'spatial sorting' of households due to flood preferences has been previously documented in the USA (Husby et al., 2018).

Johnston and Ramachandran (2014) argued that local spatial patterns of WTP estimates might exist even if global patterns of spatial significance are absent. Therefore we proceed to calculate the LISA statistics to test for locally spatially autocorrelated WTP estimates, using both the pooled and the site-specific datasets.

We test the sensitivity to the weight matrix definition. First, we found that spatial global autocorrelation results are constant when using different distance-based weight matrix definitions (k-nearest neighbour and inverse distance matrix with row normalised weights). We also tested for different numbers of neighbours used to define the spatial weight matrix (k values from 8 to 100) when estimating both global and local Moran's I statistics. The k value determines the number of nearest neighbours for each point considered in the analysis. As expected, we found that the neighbour distance increases with the k value. For example, the mean neighbour distance in the pooled dataset is 14.54 km with $k = 8$, 23.97 km with $k = 23$ and 30.24 km with $k = 30$.

Global spatial autocorrelation results are consistent for different values of k, but has a higher level of significance for $k = 23$ in the pooled dataset (see Table B.2 in Appendix S2). Although the Forth and Tay datasets do not display significant spatial autocorrelation, the Clyde dataset exhibits statistically significant global autocorrelation for the maximum number of attributes at $k = 23$ (see correlograms in Figure B.1 in Appendix S2). Furthermore, Table B.3 in Appendix S2 shows that the differences in the proportion of significant local clusters[7] in the pooled dataset are minimal and inconsequential for the purposes of our analysis. Duda et al. (2001) suggest using $k = \sqrt{n}$, as this k value is a large enough value to give a reliable result, but small enough to keep the nearest neighbours as close as possible so that distance acts as an influence factor.

Based on these findings and the Duda et al. (2001) suggestion, we report the results for $k = 23$ (closest 23 data points) in the following analysis. We used the same k value to analyse all datasets as this value maximises the global spatial correlation, and to ease the understanding of the spatial autocorrelation analysis.

Table 5 characterises all data points according to the significant local cluster types to which individuals belong, as well as identifies those individuals who are not part of any locally significant cluster. Figure B.2 in Appendix S2 presents the same information as this table, but in a visual format. Table 5 shows no cases of significant outliers in which high WTP values are surrounded primarily by low values (HL), and vice versa (LH). However, there are local statistically significant clusters of WTP estimates for improvements in all estuarine ES attributes.[8] As expected, the number of significant clusters was higher in the pooled dataset, as it is also the dataset with the largest sample size.

---

[7]Estimated as the ratio of the number of local clusters within a category and the total number of geocoded data (e.g. number of HH/number of respondents).

[8]In order to test for the robustness of our results at a regional scale of analysis (rather than a national scale), we also calculated LISA statistics to subsets of the datasets which only included the residents of the catchment areas of analysis (see Table B.4). However, the validity of these results, and the possibility to use them for estimating the summary statistics was limited by the significant reduction of the numbers of local significant clusters.
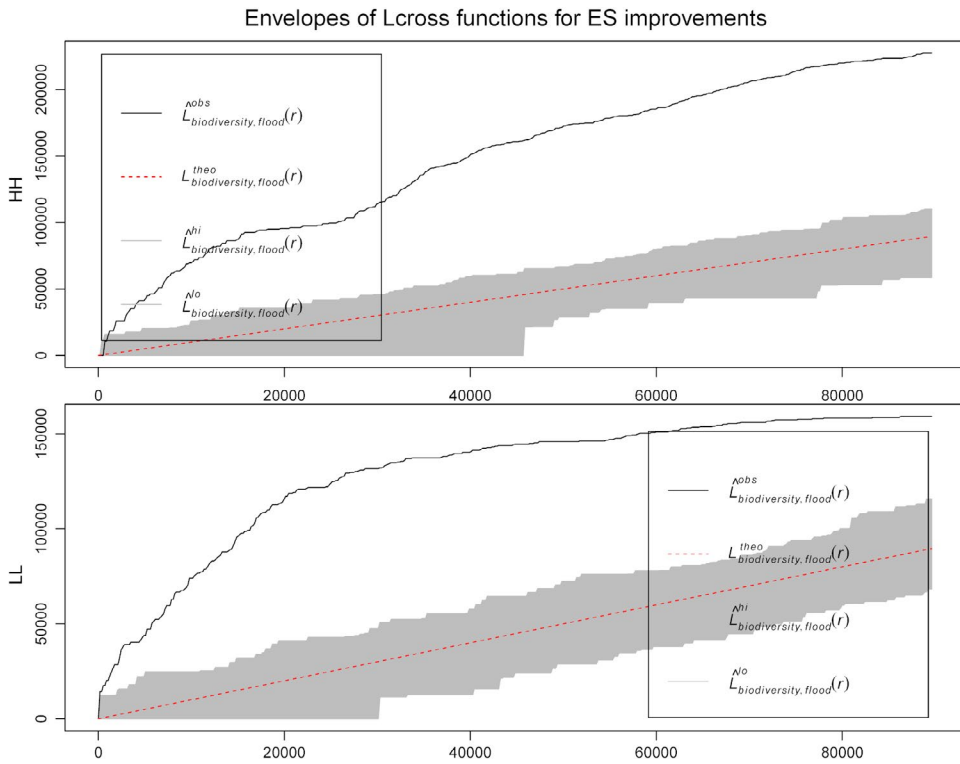
Envelopes of Lcross functions for surveys
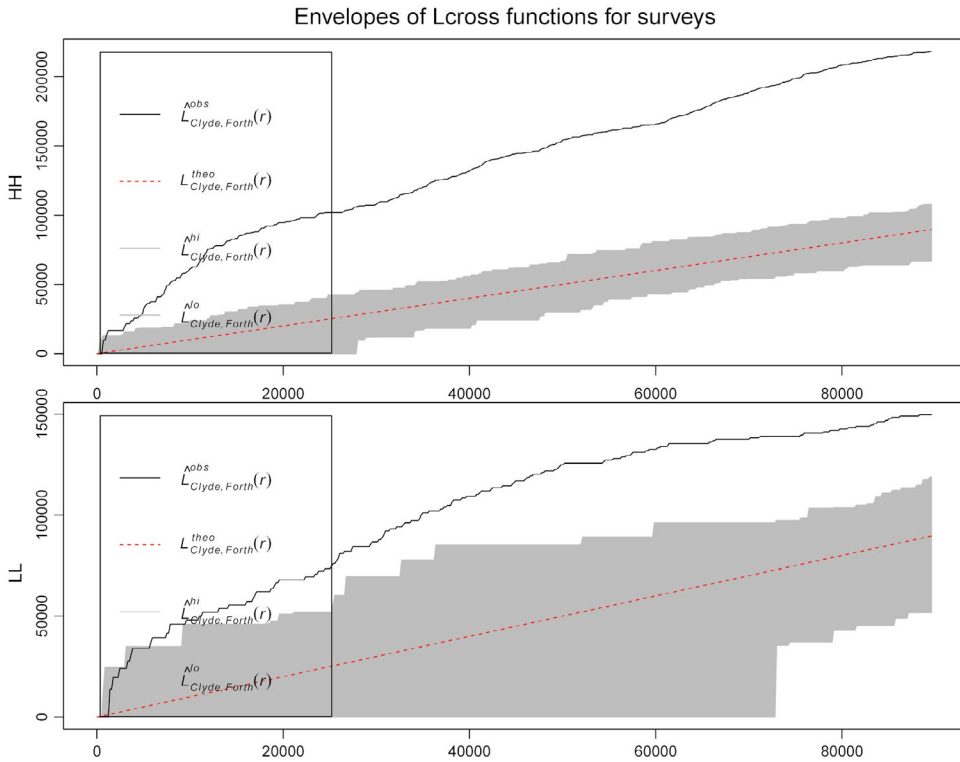
FIGURE 4 L-cross functions and envelopes for local clusters of WTP estimates marked by survey [Colour figure can be viewed at wileyonlinelibrary.com]

From Table 5, we can also infer that the total number of HH clusters identified in the pooled dataset (74) is smaller than the total number of LL clusters (80). While analysing the site-specific datasets, we can only extrapolate the trend of having a higher number of HH (over LL) when the improvements occur in the Forth catchment area. This finding is interesting and emphasises the relevance of developing multi-scale studies when exploring spatial patterns in WTP, as different patterns might only emerge when the scale of analysis is amplified (see Johnston et al., 2015).

Since we are dealing with different sample sizes for each survey, Table 5 also presents the local cluster information in a percentage format. Even if the percentage of membership to any significant local cluster is not greater than 6% of the final sample (for all attributes, levels and datasets) our results reveal the presence of hotspots and coldspots of WTP for estuarine ES improvements in Scotland. This finding suggests that respondent's preferences interact with their immediate spatial context and that they might feedback from the environmental, socio-economic and cultural features of the local setting.

The membership likelihood of HH (or LL) might be partially explained by the relative distances to the catchment area of analysis (see Figure B.2 in Appendix S2). Testing this hypothesis formally is difficult with our sample size. However, we developed an exploratory analysis using one-way ANOVA tests to evaluate whether there are significant differences in individual-specific WTP estimates at different distances to the catchment area. The results indicate that the distance decay effect is not significant for any attribute or level (see boxplots online, Figure B.3–B.8 in Appendix S2).

The significant local clusters of WTP (HH and LL) were also plotted with a selected number of socioeconomic indicators to assess whether their spatial arrangement follows the spatial distribution of the population sociodemographic characteristics (see maps in Appendix S1–S5).

FIGURE 5   L-cross functions and envelopes for local clusters of WTP estimates marked by ES [Colour figure can be viewed at wileyonlinelibrary.com]

Even though it is not possible to draw conclusions regarding the variables' correlation strength from these maps, there seems to be an overlap of hotspots with the data zones having higher percentages of older people and females. This is consistent with the user-specific ASC, which indicated that both female and older people have a significant preference for ES improvements (see Table 3).

Finally, when comparing the spatial distribution of positive and negative clusters in Figure B.2 in Appendix S2, we can identify a common trend for each cluster category. The hotspots of WTP estimates are mostly situated in densely populated areas in Scotland such as the Central Belt of Scotland (comprising the cities of Edinburgh and Glasgow) and the region close to Aberdeen. The coldspots of WTP estimates are scattered in space, but they are frequently located in less populated regions such as the Highlands and the Islands. Our findings contrast with Campbell et al. (2009), who found that larger centres of populations led to lower WTP estimates for rural landscape improvements in Ireland. However, this might be explained by the differences in the environmental management policies proposed. In our study, we use a restoration project impacting the environmental quality of Scottish cities directly (as they are located inside the potentially restored catchment areas), whereas in Campbell et al. (2009) the proposed policy focus on providing environmental improvements in rural regions of Ireland, further away from urban centres.

A preliminary visual examination of hot (cold) spots pattern plots may help to identify evident spatial trends among ES and case studies. Nonetheless, drawing general conclusions from the visual comparison of plots is not straightforward (Long & Robertson, 2018). Therefore, the subsequent analysis uses the Multi-type Ripley's K and L function (cross-type) to test whether or not there is clustering between all pairs of types (Ripley, 1981).

4.3 | Comparison of the geographical pattern of local clusters of willingness to pay for ES

In this section, we use a cross-type spatial point pattern analysis to explore whether the distribution patterns of significant hotspots (and coldspots) of WTP are similar among estuarine ES and across case studies. The summary functions K_{ij} and L_{ij} allow us to develop a pair-wise analysis of all the possible combinations of the survey point pattern types defined inside our marks ('ES-types' and 'estuary-types'). For instance, they allow us to understand the interaction between the point pattern HH_{Clyde} and HH_{Tay} if focusing on the 'estuary-types' marks, or to see whether the 'ES-types' point patterns of HH_{flood} and $HH_{biodiversity}$ are clustered together.[9] Similarly, they are used to explain the interaction between the point pattern LL_{Clyde} and LL_{Tay} if focusing on the 'estuary-types' marks, or to explore if the 'ES-types' point patterns of LL_{flood} and $LL_{biodiversity}$ are clustered together.[10]

The K and L cross-type functions were estimated for HH and LL processes, independently. Results of the K-cross functions are in line with the findings derived from the L-cross function. Since the interpretation of the L cross-type function is more straightforward than the K-cross function, and the results are similar for both functions and all possible combinations of point patterns, we only present the figures plotting the $L_{Clyde,Forth}$ and $L_{biodiversity,flood}$ cross-type functions with the simulated envelopes in the main text (see Figures 4 and 5). Please refer to Figures D.1 and Figure D.2 in Appendix S4 to find the remaining L_{ij} cross-type plots.

The plots in Figures 4 and 5 show the observed cross L function together with the theoretical Poisson L function, independently for LL and HH (see plot 1 and 2, respectively). The simulated envelopes plotted in these figures are used to test the null hypothesis of CSRI between point types, for which they add the maximum and minimum L_{ij} over the 1,000 simulation datasets to depict the upper and lower bound of the envelopes.

Figure 4 presents the pair-wise comparison of one combination of the 'estuary-types' point patterns and displays independent analysis for the points classified as HH (see plot 1) and LL (see plot 2). Figure 5 is organised similarly but, instead, it displays the L-cross plots for one combination of the 'ES-types'. In both figures (as well as in Figure D.1 and Figure D.2 in Appendix S4), it can be seen that the L-cross function is outside the simulation envelope for almost every distance band (denoted by r), when referring to hotspots as well as coldspots.

This finding suggests the existence of 'inter-ES' clustering of HH (or LL) points in addition to 'inter-estuary' clustering of HH (or LL) points, for all distances. Put another way: (i) the hotspots (or coldspots) of WTP for improvements in flood control, biodiversity and recreation commonly occur close to each other in space; (ii) the hotspots (or coldspots) of WTP for improvements in estuarine ES delivered with a restoration project happening at the Clyde, Forth and Tay catchment area also tend to occur close to each other in space.

5 | CONCLUSIONS

We investigate whether the geographical distribution of significant hot (cold) spots of WTP is similar among different ES and across case studies. Our findings reveal that the geographical distribution of WTP for ES is far more complex than indicated by previous distance decay

---

[9]Using all attributes and levels to estimate the Ripley's K and L-cross functions when analysing the 'ES-types' marks would create a large number of combinations to analyse (30 in total, or 15 for HH and LL). Instead, we merged the shapefiles containing the same type of local cluster (e.g. HH) for the two levels of the same attribute (e.g. HH-F1 and HH-F2) into one shapefile (e.g. HH flood) and used them to estimate the spatial summary functions. By doing so, we reduced the number of combinations to analyse to 12 (6 for each, HH and LL).

[10]The robustness of these results was tested by estimating a MXL model allowing for correlated coefficients. The Ripley's L-cross analysis developed with this new model leads to similar conclusions (see full analysis in Appendix S3).

studies (Bateman et al., 2006; Schaafsma et al., 2012). Instead, findings support recent claims for using non-linear approaches of analysis which account for 'patchy' patterns of clustering of environmental values (Johnston & Ramachandran, 2014; Meyerhoff, 2013).

Overall, results indicate that hot (cold) spots of WTP for improvements in the provision levels of estuarine ES tend to occur close to each other in space regardless of the ES in question, or the case study (estuary) in consideration. This sorting of preferences may be partially explained by the Tiebout-sorting theory (Tiebout, 1956) which suggests that individuals 'vote with their feet' by moving to areas that offer ES supply levels in line with their preferences. Spatial sorting due to preferences has been previously identified in the empirical environmental valuation literature (Abildtrup et al., 2013; Liu et al., 2020; Meyerhoff, 2013; Schindler et al., 2018). Additionally, sorting models have used a general equilibrium framework to explain this phenomenon in the context open space amenities (Klaiber & Phaneuf, 2010), pollutants (Smith et al., 2004) and flood protection (Husby et al., 2018).

Although the present research cannot conclude that residential sorting is causing the concentration of hotspots (or coldspots) of WTP,[11] we provide robust evidence about the persistence of spatial agglomeration of groups of neighbours with similar demand across ES, as well as case studies. That is, residents may not sort only on the basis of environmental goods preference, but they may also consider their ES preferences. Generalising this result would require further case studies.

Ignoring this local sorting of preferences towards ES (and the mechanisms behind them) would not only lead to misleading welfare estimates but could obscure important distributional aspects of environmental quality. For instance, Husby et al. (2018) found that residential sorting led to a clustering of vulnerable households in flood risk regions in the USA. They suggest that residential sorting is related to the income distribution since low-income households (who may be more vulnerable to flooding) trade off flood protection for lower housing costs to a higher degree than high-income households.

There is a further need to assess the key determinants of hotspots (or coldspots) of WTP with spatial lag models estimated in the second stage of analysis. This information could be used to design spatially targeted environmental policies that prioritise equity or efficiency concerns. Although the use of a two-stage approach of analysis allows one to develop further analysis on welfare estimates, it has to be noted that the results must be interpreted under the light of the assumptions made in the first stage of analysis (Abildtrup et al., 2013; Johnston et al., 2015) and that inferences are conditional to the accuracy of the estimation of individual-level parameters (Glenk et al., 2020). The individual-specific WTP estimates used in this analysis passed all three diagnostic tests proposed by Sarrias (2020) (see Appendix S5), which suggests the reliability of the individual-specific WTP estimates used in applied research. However, it has to be noted that the use of a fixed cost coefficient is admittedly a strong assumption and represents a limitation of this work.

Regardless of the mechanisms underlying the spatial distribution of environmental preferences, there is growing evidence about inter-neighbourhood environmental inequality in the economic literature (Crowder & Downey, 2010; Downey, 2006; Heynen et al., 2006; Strife & Downey, 2009) and the hedonic literature (Bayer et al., 2009; Gamper-Rabindran & Timmins, 2013). Future DCEs using geocoded individual-specific WTP could also contribute to this body of literature. For instance, by analysing local clusters of WTP together with data on ES supply and socio-demographics to explore whether the poor and marginalised are, in fact, concentrated in low ES supply regions.

Thinking spatially while generating environmental management plans is essential for creating efficient and optimal policies which take into consideration the spatial allocation of natural

---

[11]This would require hedonic data, as well as additional information about the provision levels of ES.

resources together with the distribution of wealth (Czajkowski et al., 2017). Exploring spatial heterogeneity patterns at finer scales allows policy-makers to design spatially targeted environmental policies and allows estimation of more accurate aggregate environmental values. However, since there is a trade-off between increasing the precision of understanding of preference heterogeneity in space and generating information with a higher degree of complexity, it becomes relevant to seek ways to summarise this information so it can be used in environmental planning. We propose using spatial summary functions to find commonalities in the geographical distribution of WTP estimates that derive from environmental valuation studies.

The increase of modelling realism while estimating welfare estimates is not only beneficial from the modelling perspective but also has real-world applications as it allows the development of 'better-informed' and 'locational targeting' of environmental policy interventions (Bateman et al., 2016). For instance, policy-makers could use the information on local clusters on WTP within multi-criteria analysis to identify a small number of regions to target or prioritise, as well as to calibrate the design of environmental taxes (Yao et al., 2014). Moreover, policy-makers could make more efficient use of public funds by developing environmental education policies aiming to promote pro-environmental behaviour in regions with higher density coldspots of WTP or environmental improvements.

ORCID
Valeria M. Toledo-Gallegos https://orcid.org/0000-0003-3267-1530

REFERENCES
Abildtrup, J., Garcia, S., Olsen, S.B. & Stenger, A. (2013) Spatial preference heterogeneity in forest recreation. *Ecological Economics*, 92, 67–77. https://doi.org/10.1016/j.ecolecon.2013.01.001

Anselin, L. (1995) Local Indicators of Spatial Association—LISA. *Geographical Analysis*, 27(2), 93–115. https://doi.org/10.1111/j.1538-4632.1995.tb00338.x

Aregay, F., Yao, L. & Zhao, M. (2016) Spatial preference heterogeneity for integrated river basin management: The case of the shiyang river basin. *China. Sustainability*, 8(12), 970. https://doi.org/10.3390/su8100970

Baddeley, A., Rubak, E. & Turner, R. (2015) *Spatial point patterns: Methodology and applications with R*. Boca Raton: Chapman and Hall/CRC Press.

Badura, T., Ferrini, S., Burton, M., Binner, A. & Bateman, I.J. (2019) Using individualised choice maps to capture the spatial dimensions of value within choice experiments. *Environmental and Resource Economics*, 75(2), 297–322. https://doi.org/10.1007/s10640-019-00358-3

Baerenklau, K.A., González-Cabán, A., Paez, C. & Chavez, E. (2010) Spatial allocation of forest recreation value. *Journal of Forest Economics*, 16(2), 113–126. https://doi.org/10.1016/j.jfe.2009.09.002

Bamière, L., David, M. & Vermont, B. (2013) Agri-environmental policies for biodiversity when the spatial pattern of the reserve matters. *Ecological Economics*, 85, 97–104. https://doi.org/10.1016/j.ecolecon.2012.11.004

Bamière, L., Havlík, P., Jacquet, F. & Millet, G. (2008) Spatially explicit farming system modelling for an efficient agri- environmental policy design INRA SFER CIRAD. In: *107. EAAE Seminar : Modeling of agricultural and rural development policies*, Seville, Spain, p. 18.

Bastian, O., Grunewald, K. & Syrbe, R.-U. (2012) Space and time aspects of ecosystem services, using the example of the EU Water Framework Directive. *International Journal of Biodiversity Science, Ecosystem Services & Management*, 8(1–2), 5–16. https://doi.org/10.1080/21513732.2011.631941

Bateman, I., Agarwala, M., Binner, A., Coombes, E., Day, B., Ferrini, S. (2016) Spatially explicit integrated modeling and economic valuation of climate driven land use change and its indirect effects. *Journal of Environmental Management*, 181, 172–184. https://doi.org/10.1016/j.jenvman.2016.06.020

Bateman, I.J., Day, B.H., Georgiou, S. & Lake, I. (2006) The aggregation of environmental benefit values: Welfare measures, distance decay and total WTP. *Ecological Economics*, 60(2), 450–460. https://doi.org/10.1016/j.ecolecon.2006.04.003

Bayer, P., Keohane, N. & Timmins, C. (2009) Migration and hedonic valuation: The case of air quality. *Journal of Environmental Economics and Management*, 58(1), 1–14. https://doi.org/10.1016/j.jeem.2008.08.004

Bergmann, A., Colombo, S. & Hanley, N. (2008) Rural versus urban preferences for renewable energy developments. *Ecological Economics*, 65(3), 616–625. https://doi.org/10.1016/j.ecolecon.2007.08.011

Besag, J. (1977) Contribution to the discussion of Dr. Ripley's paper. *Journal of the Royal Statistical Society*, B(39), 193–195.

Birol, E., Hanley, N., Koundouri, P. & Kountouris, Y. (2009) Optimal management of wetlands: Quantifying trade-offs between flood risks, recreation, and biodiversity conservation. *Water Resources Research*, 45(11), 1–11. https://doi.org/10.1029/2008WR006955

Bivand, R. & Piras, M.G. (2015) Comparing implementations of estimation methods for spatial econometrics. *Journal of Statistical Software*, 63(18), 1–36. https://doi.org/10.18637/jss.v063.i18

Bockstael, N.E. (1996) Modeling economics and ecology: The importance of a spatial perspective. *American Journal of Agricultural Economics*, 78(5), 1168. https://doi.org/10.2307/1243487

Börger, T. & Hattam, C. (2017) Motivations matter: Behavioural determinants of preferences for remote and unfamiliar environmental goods. *Ecological Economics*, 131, 64–74. https://doi.org/10.1016/j.ecolecon.2016.08.021

Botzen, W.J.W., Bergh, J. & Van Den, B.J.M. (2012) Monetary valuation of insurance against climate change risk. *International Economic Review*, 53, 1005–1025. https://doi.org/10.1111/j.1468-2354.2012.00709.x

Brouwer, R., Martin-Ortega, J. & Berbel, J. (2010) Spatial preference heterogeneity: A choice experiment. *Land Economics*, 86(3), 552–568. https://doi.org/10.1353/lde.2010.0045

Brown, G., Pullar, D. & Hausner, V.H. (2016) An empirical evaluation of spatial value transfer methods for identifying cultural ecosystem services. *Ecological Indicators*, 69, 1–11. https://doi.org/10.1016/j.ecolind.2016.03.053

Budziński, W., Campbell, D., Czajkowski, M., Demšar, U. & Hanley, N. (2018) Using geographically weighted choice models to account for the spatial heterogeneity of preferences. *Journal of Agricultural Economics*, 69(3), 606–626. https://doi.org/10.1111/1477-9552.12260

Campbell, D., Hutchinson, W.G. & Scarpa, R. (2009) Using choice experiments to explore the spatial distribution of willingness to pay for rural landscape improvements. *Environment and Planning A: Economy and Space*, 41(1), 97–111. https://doi.org/10.1068/a4038

Campbell, D., Scarpa, R. & Hutchinson, W.G. (2008) Assessing the spatial dependence of welfare estimates obtained from discrete choice experiments. *Letters in Spatial and Resource Sciences*, 1(2–3), 117–126. https://doi.org/10.1007/s12076-008-0012-6

ChoiceMetrics. (2012). Ngene 1.1.1 User manual and reference guide: The Cutting Edge in Experimental Design.

Crowder, K. & Downey, L. (2010) Interneighborhood migration, race, and environmental hazards: Modeling microlevel processes of environmental inequality. *American Journal of Sociology*, 115(4), 1110–1149. https://doi.org/10.1086/649576

Czajkowski, M. & Budzinksi, W. (2017) *Simulation Error in Maximum Likelihood Estimation of Discrete Choice Models*. Working Paper 18/2017 [247]. Available at: https://www.wne.uw.edu.pl/files/9315/0296/9268/WNE_WP247.pdf

Czajkowski, M., Budziński, W., Campbell, D., Giergiczny, M. & Hanley, N. (2017) Spatial heterogeneity of willingness to pay for forest management. *Environmental and Resource Economics*, 68(3), 705–727. https://doi.org/10.1007/s10640-016-0044-0

De Valck, J. & Rolfe, J. (2018) Spatial heterogeneity in stated preference valuation: Status, challenges and road ahead. *International Review of Environmental and Resource Economics*, 11(4), 355–422. https://doi.org/10.1561/101.00000097

De Valck, J., Vlaeminck, P., Broekx, S., Liekens, I., Aertsens, J., Chen, W. (2014) Benefits of clearing forest plantations to restore nature? Evidence from a discrete choice experiment in Flanders, Belgium. *Landscape and Urban Planning*, 125, 65–75. https://doi.org/10.1016/j.landurbplan.2014.02.006

De Valck, J., Broekx, S., Liekens, I., Aertsens, J. & Vranken, L. (2017) Testing the influence of substitute sites in nature valuation by using spatial discounting factors. *Environmental and Resource Economics*, 66(1), 17–43. https://doi.org/10.1007/s10640-015-9930-0

Downey, L. (2006) Environmental racial inequality in detroit. *Social Forces*, 85(2), 771–796. https://doi.org/10.1353/sof.2007.0003

Duda, R.O., Hart, P.E. & Stork, D.G. (2001) Pattern classification. *Pattern Analysis and Applications*, 1(2), 142–143. https://doi.org/10.1007/BF01237942

Faccioli Michela, Czajkowski Mikołaj, Glenk Klaus, Martin-Ortega Julia (2020) Environmental attitudes and place identity as determinants of preferences for ecosystem services. *Ecological Economics*, 174 106600http://dx.doi.org/10.1016/j.ecolecon.2020.106600.

Gamper-Rabindran, S. & Timmins, C. (2013) Does cleanup of hazardous waste sites raise housing values? Evidence of spatially localized benefits. *Journal of Environmental Economics and Management*, 65(3), 345–360. https://doi.org/10.1016/j.jeem.2012.12.001

Getis, A. (2010) Spatial autocorrelation. In Fischer, M., & Getis, A. (Eds.), *Handbook of Applied Spatial Analysis*, Berlin, Heidelberg: Springer, 255–278. https://doi.org/10.1007/978-3-642-03647-7_14

Glenk, K., Johnston, R.J., Meyerhoff, J. & Sagebiel, J. (2020) Spatial dimensions of stated preference valuation in environmental and resource economics: Methods, trends and challenges. *Environmental and Resource Economics*, 75(2), 215–242. https://doi.org/10.1007/s10640-018-00311-w

Google (n.d.) Map of Scotland. Available at: https://www.google.com/maps/place/Escocia/@56.6826283,-6.91698,6.82z/data=!4m5!3m4!1s0x4861e2c403f2a19f:0xe7c1fad809c30714!8m2!3d56.4906712!4d-4.2026458!5m1!1e4 (accessed 20 August 2019).

Haddad, N.M., Brudvig, L.A., Clobert, J., Davies, K.F., Gonzalez, A., Holt, R.D. et al. (2015) Habitat fragmentation and its lasting impact on Earth's ecosystems. *Science Advances*, 1(2), e1500052. https://doi.org/10.1126/sciadv.1500052

Hanley, N.D., Schläpfer, F. & Spurgeon, J. (2003) Aggregating the benefits of environmental improvements: Distance-decay functions for use and non-use values. *Journal of Environmental Management*, 68(3), 297–304. https://doi.org/10.1016/S0301-4797(03)00084-7

Hess, S. & Palma, D. (2019) Apollo: A flexible, powerful and customisable freeware package for choice model estimation and application. *Journal of Choice Modelling*, 32, 100170. https://doi.org/10.1016/j.jocm.2019.100170

Heynen, N., Perkins, H.A. & Roy, P. (2006) The political ecology of uneven urban green space: The impact of political economy on race and ethnicity in producing environmental inequality in Milwaukee. *Urban Affairs Review*, 42(1), 3–25. https://doi.org/10.1177/1078087406290729

Horne, P., Boxall, P.C. & Adamowicz, W.L. (2005) Multiple-use management of forest recreation sites: A spatially explicit choice experiment. *Forest Ecology and Management*, 207(1-2), 189–199. https://doi.org/10.1016/j.foreco.2004.10.026

Husby, T., de Groot, H.L.F., Hofkes, M.W. & Filatova, T. (2018) Flood protection and endogenous sorting of households: the role of credit constraints. *Mitigation and Adaptation Strategies for Global Change*, 23(2), 147–168. https://doi.org/10.1007/s11027-015-9667-7

Jacobs, S., Vandenbruwaene, W., Vrebos, D., Beauchard, O., Boerema, A., Wolfstein, K. et al. (2013) Ecosystem Service Assessment of TIDE Estuaries.: 90. Available at: http://www.tide-toolbox.eu/pdf/reports/ES_PDF_KW.pdf

Johnston, R.J. & Duke, J.M. (2009) Willingness to pay for land preservation across states and jurisdictional scale: Implications for benefit transfer. *Land Economics*, 85(2), 217–237. https://doi.org/10.3368/le.85.2.217

Johnston, R.J., Jarvis, D., Wallmo, K. & Lew, D.K. (2015) Multiscale spatial pattern in nonuse willingness to pay: Applications to threatened and endangered marine species. *Land Economics*, 91(4), 739–761. https://doi.org/10.3368/le.91.4.739

Johnston, R.J. & Ramachandran, M. (2014) Modeling spatial patchiness and hot spots in stated preference willingness to pay. *Environmental and Resource Economics*, 59(3), 363–387. https://doi.org/10.1007/s10640-013-9731-2

Johnston, R. J., Ramachandran, M., Schultz, E., Segerson, K. & Besedin, E. Y. (2011) Willingness to pay hot spots and the distribution of ecosystem service values: implications for benefit transfer. In: *Association of Environmental and Resource Economists Annual Meeting*, Pittsburgh, Seattle, 2011. Available at: http://www.webmeets.com/files/papers/AERE/2011/195/Johnston-et-al.-AERE-2011-Final.pdf

Johnston, R.J., Swallow, S.K. & Bauer, D.M. (2002) Spatial factors and stated preference values for public goods: Considerations for rural land use. *Land Economics*, 78(4), 481–500. https://doi.org/10.2307/3146848

Jørgensen, S.L., Olsen, S.B., Ladenburg, J., Martinsen, L., Svenningsen, S.R. & Hasler, B. (2013) Spatially induced disparities in users' and non-users' WTP for water quality improvements-Testing the effect of multiple substitutes and distance decay. *Ecological Economics*, 92, 58–66. https://doi.org/10.1016/j.ecolecon.2012.07.015

Klaiber, H. & Phaneuf, D.J. (2010) Valuing open space in a residential sorting model of the Twin Cities. *Journal of Environmental Economics and Management*, https://doi.org/10.1016/j.jeem.2010.05.002

Li, F. & Zhang, L. (2007) Comparison of point pattern analysis methods for classifying the spatial distributions of spruce-fir stands in the north-east USA. *Forestry*, 80(3), 337–349. https://doi.org/10.1093/forestry/cpm010

Liu Zhaoyang, Hanley Nick, Campbell Danny (2020) Linking urban air pollution with residents' willingness to pay for greenspace: A choice experiment study in Beijing. *Journal of Environmental Economics and Management*, 104 102383http://dx.doi.org/10.1016/j.jeem.2020.102383.

Logar, I. & Brouwer, R. (2018) Substitution effects and spatial preference heterogeneity in single- and multiple-site choice experiments. *Land Economics*, 94(2), 302–322. https://doi.org/10.3368/le.94.2.302

Long, J. & Robertson, C. (2018) Comparing spatial patterns. *Geography Compass*, 12(2), 1–18. https://doi.org/10.1111/gec3.12356

Louviere, J.J., Hensher, D.A. & Swait, J.D. (2000) *Stated choice methods: Analysis and application.* Cambridge, UK: Cambridge University Press.

Lynch, H.J. & Moorcroft, P.R. (2008) A spatiotemporal Ripley's *K*-function to analyze interactions between spruce budworm and fire in British Columbia, Canada. *Canadian Journal of Forest Research*, 38(12), 3112–3119. https://doi.org/10.1139/X08-143

Manzo, L.C. (2003) Beyond house and haven: Toward a revisioning of emotional relationships with places. *Journal of Environmental Psychology*, 23(1), 47–61. https://doi.org/10.1016/S0272-4944(02)00074-9

Manzo, L.C. (2005) For better or worse: Exploring multiple dimensions of place meaning. *Journal of Environmental Psychology*, 25(1), 67–86. https://doi.org/10.1016/j.jenvp.2005.01.002

McFadden, D. (1973) Conditional logit analysis of qualitative choice behavior. In: Zarembka, P. (Ed.) *Frontiers in econometrics.* New York: Wiley, pp. 105–142. https://doi.org/10.1108/eb028592

Meyerhoff, J. (2013) Do turbines in the vicinity of respondents' residences influence choices among programmes for future wind power generation? *Journal of Choice Modelling*, 7, 58–71. https://doi.org/10.1016/j.jocm.2013.04.010

Meyerhoff, J., Boeri, M. & Hartje, V. (2014) The value of water quality improvements in the region Berlin-Brandenburg as a function of distance and state residency. *Water Resources and Economics*, 5, 49–66. https://doi.org/10.1016/j.wre.2014.02.001

Mitchell, M.G.E., Bennett, E.M. & Gonzalez, A. (2013) Linking landscape connectivity and ecosystem service provision: Current knowledge and research gaps. *Ecosystems*, 16(5), 894–908. https://doi.org/10.1007/s10021-013-9647-2

Mitchell, M.G.E., Suarez-Castro, A.F., Martinez-Harms, M., Maron, M., McAlpine, C. & Gaston, K. J. et al. (2015) Reframing landscape fragmentation's effects on ecosystem services. *Trends in Ecology and Evolution*, 30(4), 190–198. https://doi.org/10.1016/j.tree.2015.01.011

Moran, P.A. (1950) Notes on continuous stochastic phenomena. *Biometrika*, 37(1–2), 17–23. https://doi.org/10.1093/biomet/37.1-2.17

O'Higgins, T.G., Ferraro, S.P., Dantin, D.D., Jordan, S. J. & Chintala, M. M. (2010) Habitat scale mapping of fisheries ecosystem service values in estuaries. *Ecology and Society*, 15(4), 7.

Office for National Statistics (2011) *Scotland's Census.* Office for National Statistics.

Openshaw, S. (1983) The modifiable area unit problem. *Concepts and Techniques in Modern Geography*, 38, 1–41. https://doi.org/10.1177/1077558707312501

Ord, J.K. & Getis, A. (2001) Testing for local spatial autocorrelation in the presence of global autocorrelation. *Journal of Regional Science*, 41(3), 411–432. https://doi.org/10.1111/0022-4146.00224

Ordnance Survey. (2018). Postcode Unit. Ordnance Survey, Adanac Drive, Southampton, SO16 0AS, 023 8005 5257. Available at: customerservices@ordnancesurvey.co.uk. http://data.ordnancesurvey.co.uk/ontology/postcode/PostcodeUnit (accessed 25 January 2018).

Perino, G., Andrews, B., Kontoleon, A. & Bateman, I. (2014) The value of urban green space in Britain: A methodological framework for spatially referenced benefit transfer. *Environmental and Resource Economics*, 57(2), 251–272. https://doi.org/10.1007/s10640-013-9665-8

R Core Team (2020) *R: A language and environment for statistical computing.* Vienna, Austria: R Foundation for Statistical Computing.

Renó, V., Novo, E. & Escada, M. (2016) Forest fragmentation in the lower amazon floodplain: Implications for biodiversity and ecosystem service provision to riverine populations. *Remote Sensing*, 8(11), 886. https://doi.org/10.3390/rs8110886

Revelt, D. & Train, K. (1998) Mixed logit with repeated choices: Households' choices of appliance efficiency level. *Review of Economics and Statistics*, 80(4), 647–657. https://doi.org/10.1162/003465398557735

Ripley, B.D. (1977) Modeling spatial patterns (with discussion). *Journal of the Royal Statistical Society*, B(39), 172–212.

Ripley, B.D. (1981) *Spatial statistics.* New York: John Wiley Sons.

Sarrias, M. (2020) Individual-specific posterior distributions from Mixed Logit models: Properties, limitations and diagnostic checks. *Journal of Choice Modelling*, 36, 100224. https://doi.org/10.1016/j.jocm.2020.100224

Schaafsma, M., Brouwer, R., Gilbert, A., Van den Bergh, J. & Wagtendonk, A. (2013) Estimation of distance-decay functions to account for substitution and spatial heterogeneity in stated preference research. *Land Economics*, 89(3), 514–537. https://doi.org/10.1353/lde.2013.0024

Schaafsma, M., Brouwer, R. & Rose, J. (2012) Directional heterogeneity in WTP models for environmental valuation. *Ecological Economics*, 79, 21–31. https://doi.org/10.1016/j.ecolecon.2012.04.013

Schindler, M., Le Texier, M. & Caruso, G. (2018) Spatial sorting, attitudes and the use of green space in Brussels. *Urban Forestry and Urban Greening*, 31, 169–184. https://doi.org/10.1016/j.ufug.2018.02.009

Sillano, M. & de Dios, O.J. (2005) Willingness-to-pay estimation with mixed logit models: Some new evidence. *Environment and Planning A: Economy and Space*, 37(3), 525–550. https://doi.org/10.1068/a36137

Smith, V.K., Sieg, H., Banzhaf, H.S., & Walsh, R.P. (2004) General equilibrium benefits for environmental improvements: projected ozone reductions under EPA's Prospective Analysis for the Los Angeles air basin. *Journal of Environmental Economics and Management*, 47(3), 559–584. https://doi.org/10.1016/j.jeem.2003.10.006

Strife, S. & Downey, L. (2009) Childhood development and access to nature. *Organization & Environment*, 22(1), 99–122. https://doi.org/10.1177/1086026609333340

Tiebout, C.M. (1956) A pure theory of local expenditures. *Journal of Political Economy*, 64(5), 416–424. https://doi.org/10.1086/257839

Timmins, C. & Murdock, J. (2007) A revealed preference approach to the measurement of congestion in travel cost models. *Journal of Environmental Economics and Management*, 53(2), 230–249. https://doi.org/10.1016/j.jeem.2006.08.002

Train, K.E. (2009) Individual-level parameters. In: *Discrete choice model with simulation.* Second. Cambridge University Press, pp. 259–281.

Train, K.E. & Weeks, M. (2005) Discrete choice models in preference and willingness-to-pay space. In R. Scarpa, & A. Alberini (eds.), *Applications of Simulation Methods in Environmental and Resource Economics. The Economics of Non-Market Goods and Resources*, 6, Dordrecht: Springer. https://doi.org/10.1007/1-4020-3684-1_1

Turner, B.L., Janetos, A.C., Verburg, P.H. & Murray, A.T. (2013) Land system architecture: Using land systems to adapt and mitigate global environmental change. *Global Environmental Change*, 23(2), 395–397. https://doi.org/10.1016/j.gloenvcha.2012.12.009

UK National Ecosystem Assessment (2011) *UK national ecosystem assessment synthesis of the key findings. UNEP-WCMC*. UK National Ecosystem Assessment. https://doi.org/10.1177/004057368303900411

Vollmer, D., Ryffel, A.N., Djaja, K. & Grêt-Regamey, A. (2016) Examining demand for urban river rehabilitation in Indonesia: Insights from a spatially explicit discrete choice experiment. *Land Use Policy*, 57, 514–525. https://doi.org/10.1016/j.landusepol.2016.06.017

Yao, R.T., Scarpa, R., Turner, J.A., Barnard, T.D., Rose, J.M., Palma, J.H.N. (2014) Valuing biodiversity enhancement in New Zealand's planted forests: Socioeconomic and spatial determinants of willingness-to-pay. *Ecological Economics*, 98, 90–101. https://doi.org/10.1016/j.ecolecon.2013.12.009

SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section.