Mapping preferences for the restoration of environmental damage caused by illegal dumping

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Abstract

In this paper we use a discrete choice experiment to elicit the economic benefits associated with restoring environmental damage caused by illegal dumping activities. Our study focuses on an extensive rural upland area close to Belfast, where illegal dumping activities are prevalent. Using a random parameters logit model to account for unobserved taste heterogeneity, we exploit the panel nature of the dataset to retrieve partworths, or willingness to pay (WTP) values, for every individual in the sample. We subsequently investigate the existence of spatial dependence of these estimates. As a means of benefit transfer, we also employ geostatistical methods to extend across the whole of the study area the WTP estimates derived from the collected data. The resulting data are mapped and used to illustrate the implied spatial variation and local disparities in WTP for the different approaches used to restore the environmental damage caused by illegal dumping. The geographical mapping of the results is shown to add considerably more explanatory power to the welfare estimates derived from the discrete choice experiment.

Keywords: discrete choice experiments, environmental restoration, geostatistical analysis, random parameters logit, spatial dependence, illegal dumping, willingness to pay

JEL classifications: C25, Q51, Q53

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1 Introduction

This paper reports the findings from a survey designed to examine the public's preferences associated with restoring environmental damage caused by illegal dumping activities. Our research stems from the introduction of the EU Environmental Liability Directive (2004/35/CE). By establishing a common framework of environmental liability based on the 'polluter pays' principle, this Directive has the objective of preventing and remediating environmental damage. Thus, under the Directive, liable operators are required to undertake steps to control the damage and seek to prevent further environmental deterioration. Where possible, the Directive stipulates that damaged natural resources are restored to their baseline condition. In circumstances where this is not possible, however, there is a requirement to carry out complementary remediation actions which provide a similar level of natural resources and/or services that would have been supplied if the damaged resource had been fully restored. These actions are permitted to take place at an alternative off-site location, which is geographically linked to the damaged sites. There is an additional requirement that compensatory remediation is also conducted as a means of offsetting the interim loss of natural resources and services pending recovery. Because a number of options are available under the Directive a multi-attribute approach is warranted to gauge the public's preferred restoration options. At the same time the public good and non-market nature of environmental restoration favours the use of a stated preference methodology employed for the estimation of benefits provided by restoration. For these reasons, the discrete choice experiment methodology is the preferred technique. In this paper, we report results from a discrete choice experiment that was carried out to estimate the public's willingness to pay (*WTP*) for a number of restoration options to contend with the environmental damage caused by illegal dumping. Our study focuses on an extensive rural upland area close to Belfast, where illegal dumping activities are prevalent.

While quantifying the benefits of environmental restoration is very useful for evaluating different restoration options, a further, yet often overlooked, issue pertinent to any appraisal concerns the spatial distribution of benefits. Detailed information on the spatial distribution of *WTP* is useful as it helps policy decision makers and programme administrators locate areas of value and thus allows more efficient targeting of efforts (Naidoo and Ricketts, 2006). Spatial variations in *WTP* may be a consequence of a number of underlying factors, many of which vary by spatial location. Indeed, the socio-demographic profile of respondents is likely to have a significant bearing on the geographical distribution of *WTP*. Moreover, since the occurrence of illegal dumping activities are spatially arranged (e.g., proximity to roads, housing and industry) and the severity of the damage to the environment of such activities is affected by local geographic conditions (e.g., the relief and underlying geological characteristics of the land and the proximity to water courses and the water table), it is conceivable that the benefits respondents derive from restoration will be spatially dependent. Although stated preference studies have been extended to investigate distance-decay effects (e.g., Pate and Loomis, 1997; Hanley et al., 2003; Bateman et al., 2006), the inherently spatial patterns of *WTP* are rarely clarified or addressed in stated preference studies (e.g., Eade and Moran, 1996; Bateman et al., 2002; Johnston et al., 2002). Aggregate measures of *WTP*, while useful, can obscure local patterns of heterogeneity (Troy and Wilson, 2006). Exploratory spatial data analysis provides different insights about *WTP*: its distribution, regional and local outliers, regional trends, and the level of spatial autocorrelation. Furthermore, given that the distribution of benefits are likely to be both spatially and socially uneven (Bateman et al, 2006a), evaluating the geographic nature of benefits delivers advantages from the political and policy analysis viewpoints.

Comparing spatial variations in *WTP* using discrete choice experiments typically requires separate models to be estimated for each jurisdiction and/or the inclusion of additional location variables in the econometric model (e.g., Willis and Garrod, 1999; Birol et al., 2006). While both these methods can be adequately used to compare *WTP* across a small number of jurisdictions, they are arguably less suited for making comparisons across a relatively large number of jurisdictions. In the case of separate models, relatively large samples—which are often unattainable due to budget and time constraints—would usually be needed to enable statistically robust comparisons to be made across many different regions. When using location variables, the inclusion of a relatively large number of dummy variables to represent the different regions may lead to an unreasonable increase in the number of parameters to be estimated which would reduce the statistical significance of the coefficients of the attributes one wishes to estimate.

In our analysis of the discrete choice data we use a panel random parameters logit specification to account for unobserved taste heterogeneity. We exploit the panel nature of the dataset to retrieve the WTP estimates for every individual in the sample, conditional on the individual sequence of observed choices in the discrete choice experiment. This departs from customary approaches in which the WTP estimates are normally expressed as measures of central tendency of an *a priori* distribution, such as mean or median value estimates with their computed standard errors. We subsequently investigate the existence of spatial dependence of these estimates. As a means of benefit transfer, we employ a geostatistical method known as Kriging to extend, or interpolate, across the whole of the study area the WTP estimates derived from the collected data. The resulting data are mapped and used to illustrate the implied spatial variation and local disparities in WTP for different options to contend with the illegal dumping. Evidence in this paper shows that such an approach adds additional explanatory power to the welfare estimates derived from the discrete choice experiment and overcomes the potential limitations of the approaches listed above to examine the spatial nature of WTP.

The paper is organised as follows. Section 2 outlines the empirical application, the random parameters logit model used in the analysis, and gives some methodological background on the Kriging method which we use to spatially interpolate the WTP estimates. Then, Section 3 reports the relevant model results and presents the spatial distribution of the interpolated WTP estimates. Finally, Section 4 provides a discussion and offers a number of conclusions.

2 Data and methods

2.1 Data

The discrete choice experiment exercise reported here involved several rounds of design and testing. This process began with the gathering of opinions from stakeholders. Having identified the initial attributes, a series of focus group discussions with members of the public were held. The aims of the focus group discussions were fourfold: to highlight the criteria and issues that the general public felt were of importance to the countryside surrounding Belfast; to produce and refine a list of interpretable attributes, and levels thereof, that could later be used in discrete choice experiment survey; to shed light on the best way to introduce and explain the choice tasks; and, finally, to provide a platform to test draft versions of the questionnaire. Following the focus group discussions, the questionnaire was piloted. This pilot testing had the objective of checking whether the wording and format of the questionnaire was appropriate and if respondents were able to understand the discrete choice experiment exercises.

In the final version of the questionnaire the discrete choice experiment contained one on-site restoration attributes: improvement to dump sites, and three complementary restoration attributes: wildlife habitats, water quality and outdoor recreation. For each restoration attribute, three possible levels of improvement were available. To lessen the cognitive burden on the respondent, these levels were consistent for each attribute. They were described as A LOT of improvement, SOME improvement and NO improvement.

Each of which was explained in terms of the level of improvement that would be achieved through their implementation. The cost attribute was described as a one-off increase in the respondent's Rates bill. This attribute was explicitly described as the value that the respondent would personally have to pay to implement the alternative. As a result, all ensuing welfare estimates are individual rather than household values. The discrete choice experiment consisted of a panel of six repeated choice tasks. For each choice task respondents were asked to indicate their preferred alternative. Each choice task consisted of two experimentally designed alternatives—labelled Option A and Option B. Each choice task also included a Do Nothing option—which portrayed all the restoration attributes at the NO improvement level with zero cost to the respondent. When making their choices, respondents were asked to consider only the attributes presented in the choice task and to treat each choice task independently. In an attempt to minimize hypothetical bias, respondents were also reminded to take into account whether they thought restoring the environmental damage was worth the payment asked of them and were made aware that environmental protection is embedded in an array of substitute and complementary goods.

The population of interest was the adult population in the three main District Council Areas, within which the Belfast Hills is situated. The study adopted a stratified random sample to reflect the approximate population spilt between the three jurisdictions. In total, the questionnaire was posted to a random sample of 4,000 respondents drawn from the Electoral Register. Of these, 556 usable questionnaires were obtained. Thus, the overall response rate was 14 percent, which is in line with similar mail surveys conducted in Northern Ireland.

2.2 Econometric model

Random parameters logit models provide a flexible and computationally practical econometric method, which, as described in McFadden and Train (2000), with adequate data quality, may in principle be used to approximate any discrete choice model derived from random utility maximization. The random parameters logit model obviates the three limitations of standard multinomial logit by allowing for random taste variation, unrestricted substitution patterns, and correlation in unobserved factors (Train, 2003). Random parameters logit models do not exhibit the strong assumptions of independent and identically distributed (*iid*) error terms and its equivalent behavioural association with the independence of irrelevant alternatives (IIA) property. Such models also accommodate the estimation of individual-specific preferences for individual n by deriving the conditional distribution based (within sample) on their known choices x_n and y_n (i.e., prior knowledge) (e.g., Train, 2003; Hensher and Greene, 2003; Sillano and Ortúzar, 2005; Hensher et al., 2006). These conditional parameter estimates are strictly same-choice-specific parameters, or the mean of the parameters of the sub-population of individuals who, when faced with the same choice task, made the same choices. This is an important distinction since it is impossible to establish, for each individual, their unique set of estimates but rather identify a mean, and standard deviation, estimate for the sub-population who made the same set of choices in the panel (Hensher et al., 2005). Individual-specific *WTP* estimates can be achieved by applying Bayes' theorem to derive the expected value of the ratio between the restoration attribute parameter estimate (φ) and the parameter estimate for the cost attribute (γ) for individual n:

$$E\left[WTP_n\right] = E\left[-\frac{\varphi_n}{\gamma_n}\right] = \int\limits_{\beta_n} \beta_n P\left(\beta_n | y_n, x_n\right)\, d\beta_n, \tag{1}$$

where β_n is a vector of parameters for individual n. It is well known that given two outcomes A and B, Bayes' theorem relates $P(B|A)$ to the conditional probability of $P(BA)$ and the two marginal probabilities $P(A)$ and $P(B)$ as follows:

$$P(B|A) = \frac{P(A|B)P(B)}{P(A)}. \tag{2}$$

So, substituting in

$$\begin{aligned} E\left[WTP_n\right] = E\left[-\frac{\varphi_n}{\gamma_n}|y_n, x_n\right] &= \int\limits_{\beta_n} -\frac{\varphi_n}{\gamma_n}\frac{P\left(y_n, x_n|\beta_n\right)}{P\left(y_n, x_n\right)}\, d\beta_n \\ &= \int\limits_{\beta_n} -\frac{\varphi_n}{\gamma_n}\frac{P\left(y_n, x_n|\beta_n\right)P\left(\beta_n\right)}{\int\limits_{\beta_n} P\left(y_n, x_n\right)P\left(\beta_n\right)\, d\beta_n}\, d\beta_n \\ &= \frac{\int\limits_{\beta_n} -\frac{\varphi_n}{\gamma_n} P\left(y_n, x_n\right)P\left(\beta_n\right)\, d\beta_n}{\int\limits_{\beta_n} P\left(y_n, x_n|\beta_n\right)P\left(\beta_n\right)\, d\beta_n}. \end{aligned} \tag{3}$$

With knowledge of the parameter estimates this can be approximated by simulation as follows:

$$\hat{E}\left[WTP_n\right] = \frac{\frac{1}{R}\sum\limits_{R} -\frac{\hat{\varphi}_n}{\hat{\gamma}_n} L\left(\hat{\beta}_{nr}|y_n, x_n\right)}{\frac{1}{R}\sum\limits_{R} L\left(\hat{\beta}_{nr}|y_n, x_n\right)}, \tag{4}$$

where L is the logit probability and R is the number of repetitions or draws.

In this way the individual-specific WTP estimates are obtained conditional on all the information from the discrete choice experiment interview. In this paper such probabilities are approximated in estimation by simulating the log-likelihood with 100 Halton draws. For further details on Halton sequences see (Bhat, 2001, 2003).

A key element of the random parameters logit model is the assumption regarding the distribution of each of the random parameters. Random parameters can take a number of predefined functional forms, the most popular being normal and lognormal. However, it is well known that these mixing distributions can imply behaviourally inconsistent WTP values, due to the range of taste values over which the distribution spans (Train and Weeks, 2005). This is due to the presence of a share of respondents with the 'wrong' sign under normal distributions, and the presence of fat tails under lognormal distributions. This is of particular importance in a study concerned with improvements from the status-quo, on which taste intensities are expected to be positive. After evaluating the results from various specifications and distributional assumptions, we follow Hensher and Greene (2003) and opt for a bounded triangular distribution in which the location parameter is constrained to be equal to its scale. While this constraint prevents the testing of the statistical significance of the scale parameters, it forces the distribution to be bounded over a given orthant, the sign of which is the same as the sign of the location parameter thus ensuring strictly positive *WTP* values across the entire distribution.

To allow for heterogeneous preferences among respondents for all attributes within the discrete choice experiment, they are all specified as random. In practice, for all random parameters associated with the environmental restoration it is assumed that $\beta \sim \tau(\theta)$, where θ is both the location and scale parameter of the triangular distribution $\tau(\cdot)$. This includes the cost attribute, which is bounded to the negative orthant. See Hensher and Greene (2003) and Hensher et al. (2005) for a description of the triangular distribution in this context.

2.3 Spatial interpolation

To elucidate the geographical dimension of *WTP*, the individual-specific *WTP* estimates are spatially interpolated. With spatial interpolation, the individual-specific *WTP* values can be used as a method of benefit transfer by predicting *WTP* values for all locations in the study area. The interpolation method of ordinary Kriging is adopted for this study because our *a priori* expectations are that the *WTP* values exhibit a degree of spatial autocorrelation. Moreover, in comparing interpolators for spatial hedonic house price models, Anselin and Gallo (2006) find Kriging to yield the most reasonable parameter signs and magnitudes of *WTP*. Kriging is a geostatistical technique that is based on the assumption that nearby values contribute more to the interpolated values than distant observations. In other words, sampled respondents who live in close proximity should have a smaller difference in *WTP* than those farther away from one another. Kriging can thus be used for benefit transfer by predicting *WTP* across an entire study area. In Kriging the surrounding measured values are weighted to derive a prediction for an unmeasured location. The general Kriging formula used to interpolate the *WTP* values is formed as a weighted sum of the data. This is given by equation (5):

$$\hat{Z}\left[WTP_0\right] = \sum_{i=1}^{n} \omega_i Z\left(WTP_i\right), \tag{5}$$

where $\hat{Z}\left[WTP_0\right]$ is the predicted *WTP* estimate at an unsampled location, ω_i is an unknown weight for *WTP* at the i^{th} location, $Z\left(WTP_i\right)$ is the individual-specific *WTP* at the i^{th} sample point and n is the number of measured values. A further rational for using Kriging is that it is considered an optimal spatial interpolation technique since it provides the best linear unbiased estimate (BLUE) of the value of *WTP* at any point in the coverage (Burrough and McDonnell, 2000). In this analysis, ordinary Kriging is conducted using a spherical model variogram. For further discussion on the theory of Kriging and its implementation see Isaaks and Srivastava (1989), Cressie (1993) and Wackernagel (1995).

3 Results

3.1 Estimation results

Results from the random parameters logit model are presented in Table 1. The model is statistically significant and has an acceptable model fit (ρ^2 value of 0.466). Furthermore,

Table 1: Random parameters logit model results

	Mean		Scale	
Attribute	beta	t-ratio	beta	t-ratio
Dump sites: A lot of improvement	1.161	13.825	1.161	13.825
Dump sites: Some improvement	0.297	6.342	0.297	6.342
Water quality: A lot of improvement	0.824	13.296	0.824	13.296
Water quality: Some improvement	0.146	3.195	0.146	3.195
Wildlife habitats: A lot of improvement	0.910	14.533	0.910	14.533
Wildlife habitats: Some improvement	0.066	1.484	0.066	1.484
Outdoor recreation: A lot of improvement	0.203	3.763	0.203	3.763
Outdoor recreation: Some improvement	0.175	3.819	0.175	3.819
Cost	-0.040	-9.290	-0.040	-9.290
ℓ		-1,898		
χ^2		3,310[a]		
ρ^2		0.466		
AIC		1.179		
BIC		1.196		

[a] critical value equal to 16.92 $\left(\chi^2_{9,0.05}\right)$

it significantly outperforms the basic multinomial logit model—where ℓ was estimated at $-2,010$. An examination of the parameters reveals that they are all statistically significant, with positive signs—implying that, *ceteris paribus*, respondents prefer environmental damage caused by illegal dumping activities to be restored than left in an unimproved state. As respondents had higher preferences for the A LOT of improvement level *vis-à-vis* the SOME improvement level for all restoration attributes, theoretical expectations of marginal utilities are also observed. As may be seen, results indicate that respondents have much stronger preferences for restoring sites where the illegal dumping occurs compared to any of the complementary off-site restoration options. Importantly, the cost attribute is significant and in line with *a priori* expectations.

Table 2 reports summary statistics of the individual-specific *WTP* estimates. As can be seen, the implied monotonicity in the magnitude of *WTP* for the two levels of improvement is adequately reflected for all attributes, which is consistent with earlier inferences. Assessment of the implied preference orderings highlights the much stronger preferences for on-site restoration. Comparable *WTP* estimates are found for improving water quality and wildlife habitats. Lowest values are observed for improving outdoor recreation.

3.2 Spatial distribtion of *WTP*

To detect whether the estimated *WTP* are spatially autocorrelated the Moran's I statistic are reported in Table 3. The spatial weights matrix used to impose the neighbourhood structure consists of the five nearest respondents. For all restoration attributes, the Moran's I statistics are positive, with significant z-values. Accordingly, this substantiates the existence of strong positive spatial autocorrelation processes and spatial clustering of *WTP* for restoring environmental damage caused by illegal land-filling activities. As revealed by the magnitude of the Moran's I, there appears to be a higher degree of spatial autocorrelation, and hence global clustering, associated with complementary off-site

Table 2: Summary statistics of *WTP*

	Mean (£)	Standard deviation (£)	Coefficient of variation (%)
Dump sites: A lot of improvement	43.65	21.27	48.744
Dump sites: Some improvement	11.37	4.86	42.740
Water quality: A lot of improvement	31.83	15.79	49.613
Water quality: Some improvement	5.68	2.48	43.721
Wildlife habitats: A lot of improvement	32.44	10.38	32.013
Wildlife habitats: Some improvement	2.53	1.06	41.795
Outdoor recreation: A lot of improvement	7.42	2.52	33.991
Outdoor recreation: Some improvement	6.82	3.18	46.669

Table 3: Spatial autocorrelation in the *WTP* estimates

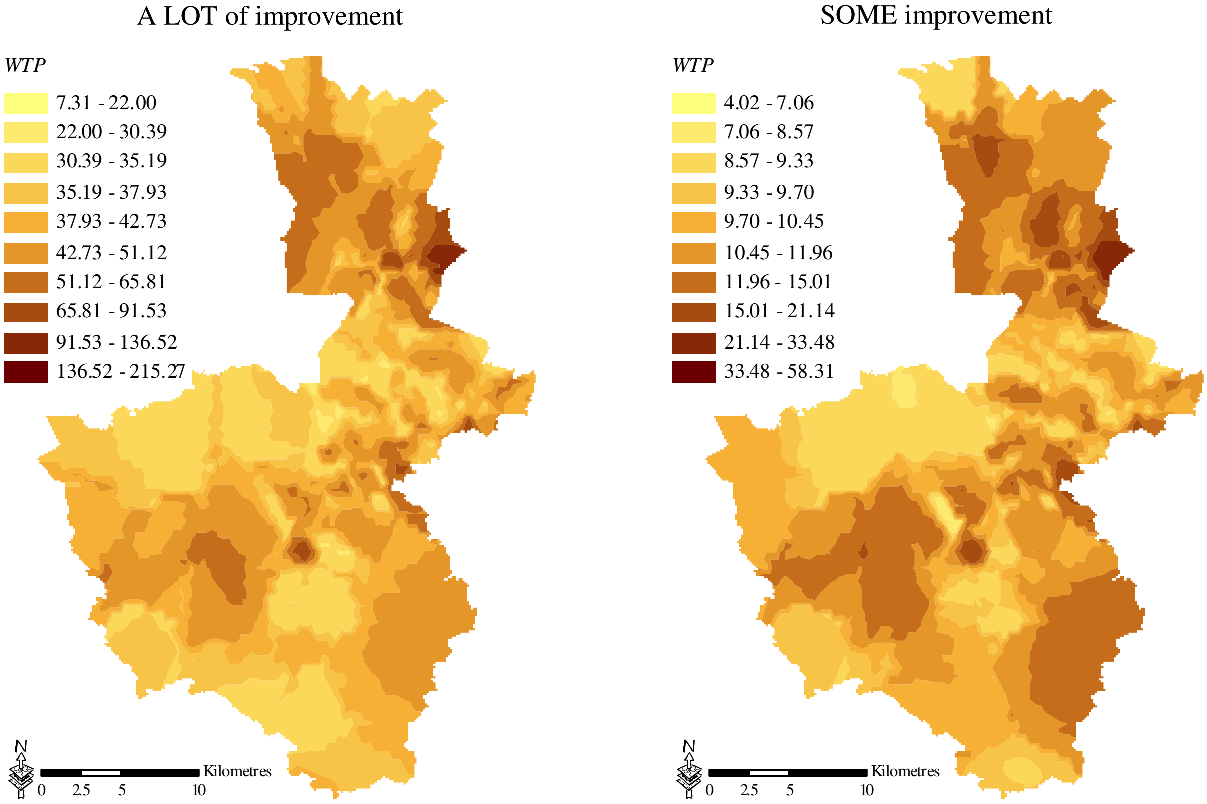
Attribute	Moran's I	z
Dump sites: A lot of improvement	0.069	2.711
Dump sites: Some improvement	0.125	5.180
Water quality: A lot of improvement	0.146	6.246
Water quality: Some improvement	0.159	6.541
Wildlife habitats: A lot of improvement	0.046	1.996
Wildlife habitats: Some improvement	0.152	6.372
Outdoor recreation: A lot of improvement	0.087	3.799
Outdoor recreation: Some improvement	0.158	6.449

restoration *vis-à-vis* on-site restoration. Moreover, the individual-specific *WTP* estimates for improvements at the SOME level of improvement are noticeably more spatially autocorrelated than those at the A LOT level of improvement.

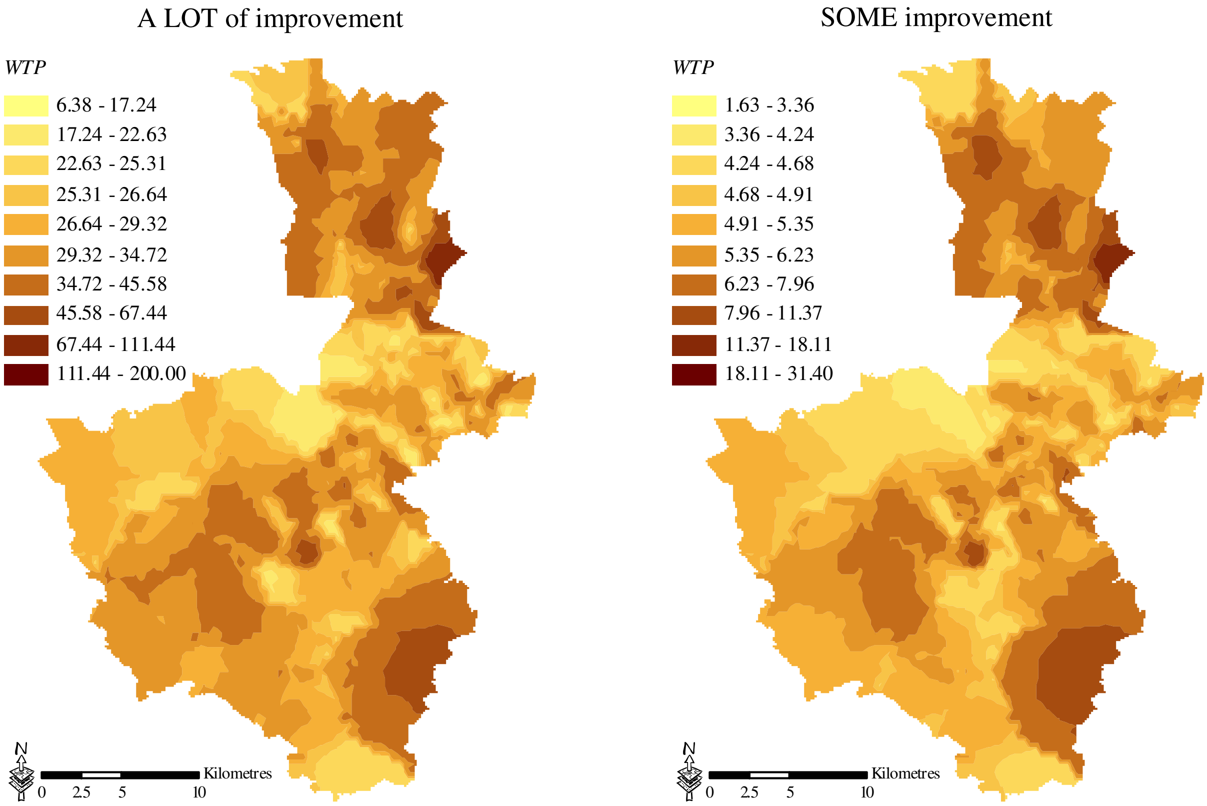
The Kriged surfaces of *WTP* across the study area for all restoration attributes are displayed in Figure 1. The stratifications represent geometric intervals, with progressively darker shades corresponding with progressively higher *WTP* values. Visualisation of the Kriged surfaces clearly indicates that the relative magnitudes of the *WTP* values appear to be quite consistent across attributes. This suggests that the relative intensities of tastes for the different restoration options are correlated across space. A further discernible finding is the varying degrees of geographical variability and concentration in *WTP* for the different restoration options. Importantly, areas of high *WTP* coincide with areas where there is a high incidence of pollution caused by illegal dumping. Therefore, the spatial distribution of respondent's *WTP* reflects their proximity to the Belfast Hills—in particular, their proximity to sites where illegal dumping is prevalent and environmental damage caused by the sites is more evident. Whereas there is a strong indication that *WTP* values for improvements concerning water quality are spatially diverse, the pattern is less striking for outdoor recreation. Correspondingly, we also observe substantial differences in the coefficients of variation (Table 2) and the extent of spatial autocorrelation (Table 3) between these two restoration options.

Validation results of the Kriged surfaces of *WTP* are summarised in Table 4. For all attributes the mean error and mean standardised errors are small indicating that sufficient observations were available to generate robust Kriged surfaces with low estimation bias.

Figure 1: Spatial distributions of *WTP*

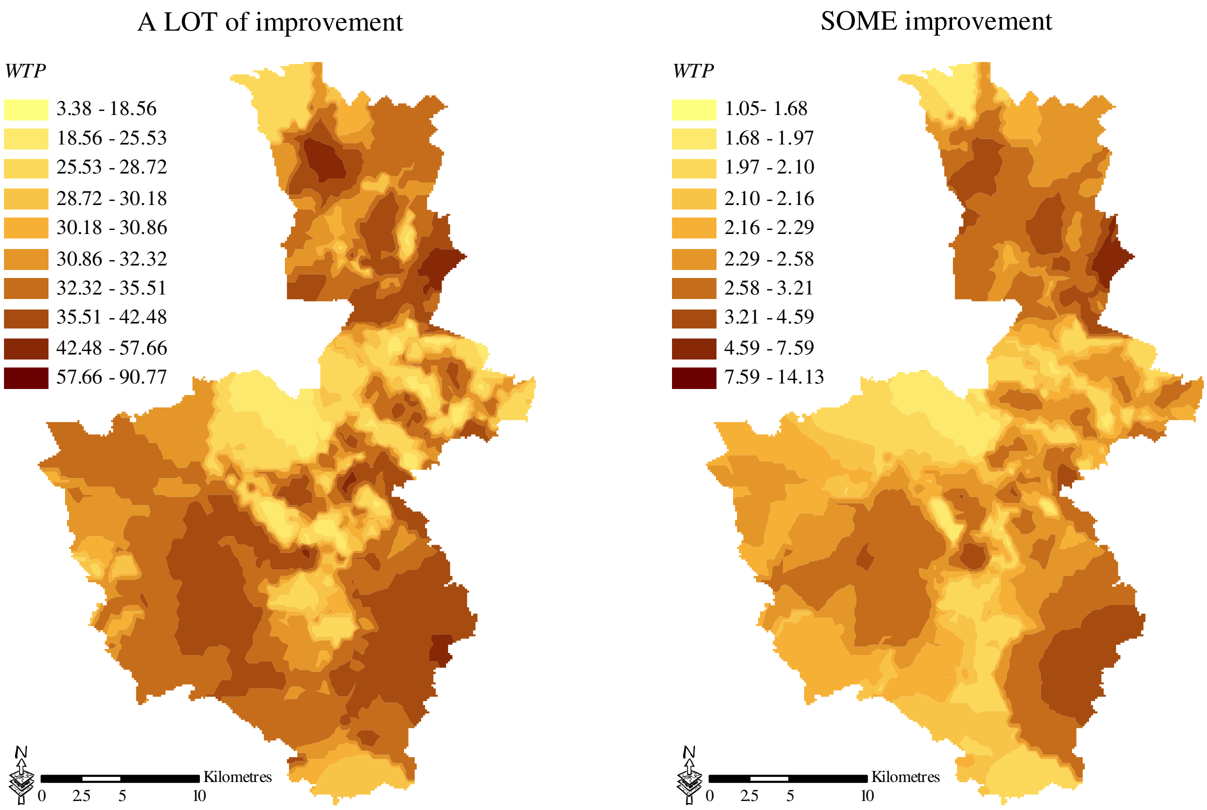


(a) Dump sites

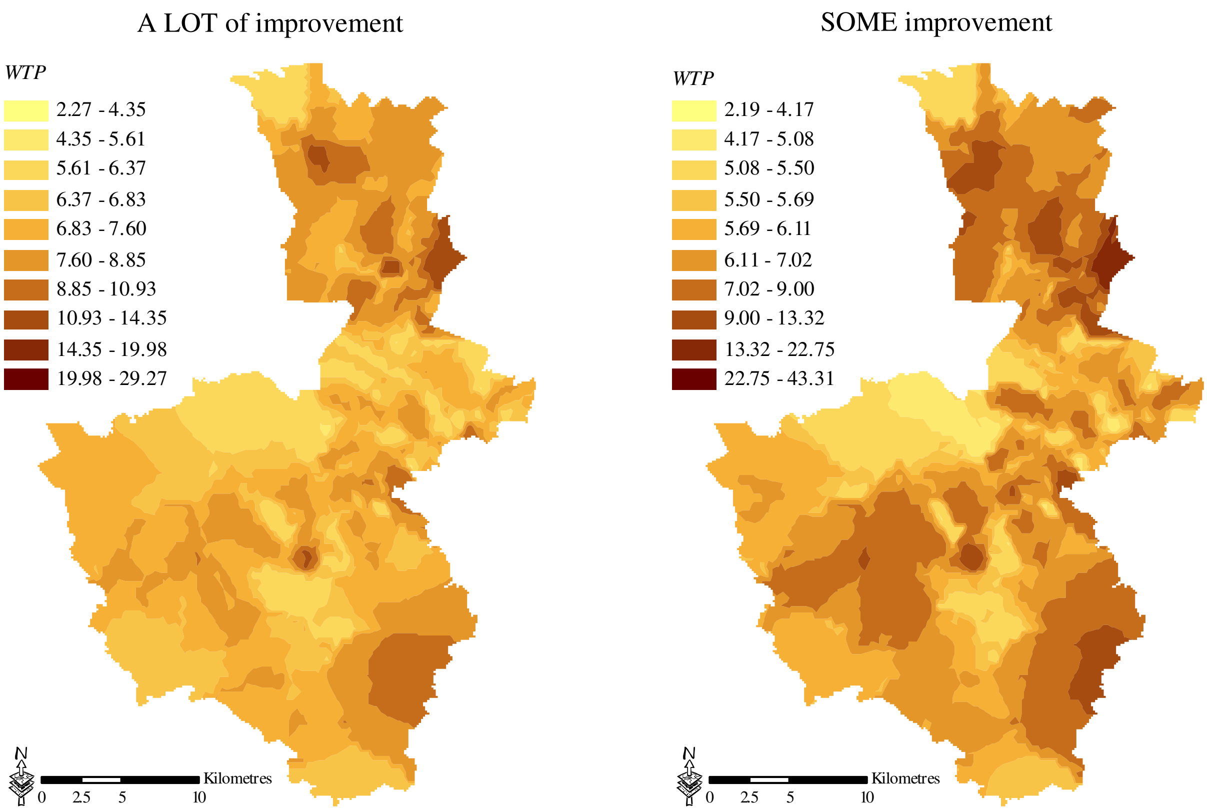


(b) Water quality

Figure 1: Spatial distributions of *WTP* (con't)



(c) Wildlife habitats



(d) Outdoor recreation

Table 4: Validation results for ordinary Kriging

	Error		Standardised error	
Attribute	Mean	Variance	Mean	Variance
Dump sites: A lot of improvement	0.143	498.182	0.067	1.348
Dump sites: Some improvement	0.015	24.265	0.002	1.535
Water quality: A lot of improvement	0.024	247.748	0.001	1.669
Water quality: Some improvement	0.001	6.096	-0.001	1.780
Wildlife habitats: A lot of improvement	-0.072	124.323	-0.007	1.156
Wildlife habitats: Some improvement	-0.002	1.111	-0.004	1.680
Outdoor recreation: A lot of improvement	0.016	6.933	0.007	1.457
Outdoor recreation: Some improvement	-0.002	9.935	-0.003	1.796

4 Discussion and conclusions

The study was designed to provide straightforward insight into the public's *WTP* to restore environmental damage caused by illegal dumping in the Belfast Hills and, as addressed in this paper, the spatial distribution of these values. This was achieved by using a random parameters logit specification along with the Kriging method of spatial interpolation. Evidence from our data demonstrates that mapping *WTP* estimates derived from discrete choice experiments is a valuable tool which adds considerably more explanatory power to welfare estimates. In particular, mapping *WTP* showed evidence of spatial dependence, which insinuates spatially dynamic intensities of tastes for the different restoration attributes. Results also indicate that the approach discussed herein provides a robust means of benefit transfer, by predicting *WTP* across the entire study area.

The results reported in this paper also have important policy implications. The spatial information can inform policy and land-use decisions but is currently lacking in most stated preference studies. Illegal dumping poses a complex logistical and costly problem for local authorities. The results provide signals for policy makers regarding the economic magnitude and spatial distribution of the local economic value of and, thus, how to maximise their efforts. We find that *WTP* for restoring environmental damages caused by illegal dumping are not evenly distributed as they vary enormously across the study area.

Findings in this paper show that there is a remarkable distance decay in *WTP* as one moves further from areas where illegal dumping is prevalent. This finding raises an important debate over the fundamental nature of environmental values and the design of policies for their preservation. This concerns the question as to whether human value in the environment is found in the pure existence of environmental features or in its appreciation through active use which takes the form of frequent visual inspection and human interaction. Our finding would indicate that this use value is a very important component of value.

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