Using geographically weighted choice models to account for the spatial heterogeneity of preferences

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Abstract

In this paper, we investigate the prospects of using geographically weighted choice models for modelling of spatially clustered preferences. We argue that this is a useful way of generating highly-detailed spatial maps of willingness to pay for environmental conservation, given the costs of collecting data. The data used in this study comes from a discrete choice experiment survey regarding public preferences for the implementation of a new country-wide forest management and protection program in Poland. We combine it with high-resolution spatial data related to local forest characteristics. Using locally estimated discrete choice models we obtain location-specific estimates of willingness to pay (WTP). Variation in these estimates is explained by characteristics of the forests in their place of residence. The results are compared with those obtained from a more typical, two stage procedure which uses Bayesian posterior means of the mixed logit model random parameters to calculate location-specific estimates of WTP. We find that there are indeed strong spatial patterns to the benefits of changes in management to national forests. People living in areas with more species-rich forests and those living nearer to higher areas of mixed forests have significantly different WTP values than those living in other locations. This kind of information enables a better distributional analysis of the gains and losses from changes to natural resource management, and better targeting of investments in forest quality.

Keywords: discrete choice experiment, contingent valuation, willingness to pay, spatial heterogeneity of preferences, forest management, passive protection, litter, tourist infrastructure, mixed logit, geographically weighted model, weighted maximum likelihood, local maximum likelihood

JEL classification: Q23, Q28, I38, Q51, Q57, Q58

Highlights:

- A discrete choice experiment related to forest management and protection in Poland is conducted
- The spatial heterogeneity of respondents' preferences and willingness to pay is investigated
- The possibility to use the geographically weighted multinomial choice model is explored and compared with the typical 2-step approach
- The analysis highlights advantages and disadvantages of the two approaches

Introduction

Preferences for environmental goods are likely to display spatial patterns such as clustering. One reason for this is that since there are differences in the spatial configuration of these goods. Peoples' preferences can be expected to adapt to their local environments (Nielsen, Olsen and Lundhede, 2007) and to the availability of substitutes (Munro and Hanley, 1999). So, for instance, living in an area with high levels of forest cover may induce people to value the conservation of forests more highly than those who live in less-forested landscapes. Another line of reasoning concerns residential sorting: people's preferences for environmental goods partly determine where they choose to live, so that measures of preferences tend to be correlated with measures of environmental quality or with distance to environmental amenities (Timmins and Murdock, 2007; Timmins and Schlenker, 2009; Baerenklau *et al.*, 2010). These two views on the reasons why spatial patterns are present in values and preferences for the environment can be thought of as different perspectives in the *directional drivers* which link values with environmental features.

From the policy and management perspective, enhancing our ability to produce detailed spatial maps of willingness to pay is important. For instance, national forest planners might want to target forest regeneration or investments in forest recreational resources in areas where the benefits of such actions would be highest. National water quality managers might, similarly, be interested in targeting costly actions to reduce pollution in a way which reflects the variation in values across a population. The application of benefit-cost thinking to spatial planning indeed requires such highly disaggregated benefits information. However, given the costs of undertaking a large number of original Willingness to Pay surveys at multiple sites, there is an interest in new methods which allows spatial maps of values to be generated in a data-efficient manner as a form of benefits transfer.

Accounting for spatial dependencies is insightful for various reasons, including in the aggregation of benefits, as illustrated by Bateman et al. (2006) in terms of identifying what "relevant population" of beneficiaries from a resource quality change should be considered. One of the most commonly encountered examples is the distance decay relationship (e.g., Jørgensen *et al.*, 2013). However, distance is not the only spatial factor which should be considered. For example, availability of site substitutes can vary across space, and it is likely to influence willingness to pay considerably. However, because in most applied cases researchers are not able to account for all possible spatial factors, there is a need for a method, which would allow to take into account different spatial dimensions of preferences, with possible nonlinear relationships and clusters.

Recent developments in Geographical Information Science (GIScience) allow the researcher to obtain rich datasets containing detailed information about the spatial configuration of environmental goods and indeed in the socio-economic characteristics of households, and then use these to investigate spatial patterns in stated and revealed preferences for such environmental goods. In this paper, we employ a method which, while widely used in other areas of social science, remains relatively unknown in agricultural and resource economics: Geographically Weighted Regression (GWR) as proposed by Fotheringham, Charlton and Brunsdon (1998). Specifically, we apply geographical weighting to choice models to investigate the spatial relationship of willingness to pay for landscape characteristics, using the example of national forest management in Poland. The rationale of this statistical approach is that, if spatial clusters of preferences do exist, a locally-weighted maximum likelihood method can be used to derive location-specific estimates. Estimation of such models can provide us with insight regarding multiple possible spatial patterns of preferences and welfare measures. This is a semi-parametric approach in that no *a priori* assumptions about the spatial distribution of preferences are made.

Economists have used a number of ways for spatial value interpolation and mapping (Johnston and Ramachandran, 2014). This includes the use of micro-simulation methods such as combinatorial optimization, as used by Hynes, Hanley and O'Donoghue (2010) for spatial aggregation on contingent valuation survey data and a "two stage" analysis, which involves estimating a Mixed Logit (MXL) model to derive location-specific WTP values, and using these WTP estimates as dependent variables in a GIS-based spatial regression (see for example Campbell, Hutchinson and Scarpa (2009) and Czajkowski *et al.* (forthcoming-a)). The relevant question is thus whether the geographical weighting approach offers advantages relative to existing methods. We therefore compare the results obtained using geographically weighted multinomial logit (GWMNL) model with the latter, "two stage" approach. This comparison reveals that although there are similarities in the spatial distributions of preferences identified using the two methods, the results differ in several important ways.

Geographically weighted models in the literature

Geographically weighted models belong to the general class of "locally estimated" models. These recognize that the relationships between analyzed variables may be highly nonlinear which are therefore difficult to represent parametrically. Early examples of such models consist of use of spline functions (Wahba, 1990), LOWESS regression (Cleveland, 1979) and kernel regressions (Fan and Gijbels, 1996). The geographically weighted approach differs, because it recognizes nonlinear relationships with respect to spatial dimensions.

Early applications of geographically weighted models were based solely on linear local models. They were used for analysis of morbidity (Fotheringham, Charlton and Brunsdon, 1998), house price data (Brunsdon, Fotheringham and Charlton, 1999), economic growth (LeSage, 1999), school performance (Fotheringham, Charlton and Brunsdon, 2001) and urban temperatures (Páez, Uchida and Miyamoto, 2002). In the context of non-market valuation, this approach has been used with hedonic price models of house prices in Cho, Poudyal and Roberts (2008) or Saphores and Li (2012).

Local likelihood models were introduced by Fan, Heckman and Wand (1995) and Fan, Farmen and Gijbels (1998). These use weighted maximum likelihood estimators for inference. Applications of these techniques in discrete choice models are very limited, and were undertaken mostly in context of transportation. Locally estimated models are used either to recover WTP distribution non parametrically such as in Fosgerau (2007), Börjesson, Fosgerau and Algers (2012) and Koster and Koster (2015) or to analyze behavioral tendencies such as the implications of prospect theory (Hjorth and Fosgerau, 2012) and preference dynamics (Dekker, Koster and Brouwer, 2014). However, none of these approaches used local discrete choice models to analyze spatial heterogeneity – the issue considered in the present paper. Geographically weighted models for discrete response variables have been employed in the past, but in rather different contexts, not connected with valuation of public goods, such as modelling urban growth (Luo and Kanala , 2008) or predicting land use changes (Wang, Kockelman and Wang, 2011).

Methodology

We begin this section with a description of the geographically weighted multinomial logit. We follow this with an explanation of the two-stage approach using location-specific WTP estimates retrieved from the MXL model.

The Geographically weighted multinomial logit model

GWMNL model is defined as follows. A respondent *n*'s utility from choosing alternative *i* in the *j*-th choice task is given by:

$$U_{ijn} = V_{ijn} + \varepsilon_{ijn} = \boldsymbol{\beta}_l{}' \mathbf{X}_{ijn} + \varepsilon_{ijn}\,, \tag{1}$$

where the error term ε_{ijn} is assumed to be i.i.d with a Gumbel distribution. $\boldsymbol{\beta}_l$ is a set of parameters for location *l*. The assumption which allows for the estimation of such a model is that individuals located close to each other are assumed to have more similar preference parameters than individuals located far away from each other, which is consistent with either of the directional drivers in the introduction. As a result, the parameters become spatially correlated. For convenience and ease of comparison between this approach and the approach used in Campbell, Hutchinson and Scarpa (2009) and Czajkowski *et al.* (forthcoming-a) (described in detail below) we estimated the GWMNL in WTP-space (Train and Weeks, 2005). This means that equation (1) was reformulated as:

$$\begin{aligned} U_{ijn} &= \boldsymbol{\beta}_l^{\text{non-cost}} \mathbf{X}_{ijn}^{\text{non-cost}} - \beta_l^{\text{cost}} X_{ijn}^{\text{cost}} + \varepsilon_{ijn} = \\ &= \beta_l^{\text{cost}} \left(\frac{\boldsymbol{\beta}_l^{\text{non-cost}}}{\beta_l^{\text{cost}}}' \mathbf{X}_{ijn}^{\text{non-cost}} - X_{ijn}^{\text{cost}} \right) + \varepsilon_{ijn} = \beta_l^{\text{cost}} \left(\boldsymbol{\alpha}_l' \mathbf{X}_{ijn}^{\text{non-cost}} - X_{ijn}^{\text{cost}} \right) + \varepsilon_{ijn} \end{aligned} \tag{2}$$

where now $\boldsymbol{\alpha}_{l,}\, \beta_l^{\text{cost}}$ are parameters to be estimated.

Estimation of the GWMNL model is conducted by estimating *L* 'local' models, where *L* is a number of distinct locations. In the case of our study, there were 253 distinct locations of respondents (unique postal codes) and therefore this is the number of the local models. Each local model is estimated via the weighted maximum likelihood method. The likelihood of individual *n* making a choice in a *j-th* choice task in the *l-th* local model is given by a standard multinomial logit formula:

$$L_{j,n}^{l} = \prod_{i=1}^{I} \left(\frac{\exp\left(\boldsymbol{\beta}_l{}' \mathbf{X}_{ijn}\right)}{\sum_k \exp\left(\boldsymbol{\beta}_l{}' \mathbf{X}_{kjn}\right)} \right)^{y_{ijn}} . \tag{3}$$

The weighted log-likelihood for *l-th* model is defined as follows:

$$WL^{l} = \sum_{n=1}^{N} \sum_{j=1}^{J} \lambda\left(Lat_n, Long_n, b, l\right) \log\left(L_{j,n}^{l}\right), \tag{4}$$

where $\lambda\left(Lat_n, Long_n, b, l\right)$ is a geographical weight (kernel), which depends on latitude and longitude of individual *n*'s location, b which is called the 'bandwidth parameter' and the location *l* for which the local model is estimated. In order to take the panel nature of the data into account, we have calculated robust standard errors that are clustered at the individual level. Note that geographically weighted models normally use projected data, with the location given as metric coordinates *X* and *Y* (easting and northing), to avoid having to use the complex and computationally time-consuming 3D calculation of geographic distance with the two angular coordinates (latitude and longitude) and indeed this was the same in our case. However, for clarity and to avoid potential confusion with independent variables $\mathbf{X}_{ijn}$ we refer to the two projected coordinates (X and Y) here as longitude and latitude respectively. There are a few functional forms of $\lambda(\cdot)$ proposed in the literature. In what follows, we use the Gaussian kernel defined as:

$$\lambda\left(Lat_n, Long_n, b, l\right) = \exp\left(-0.5 \frac{\left(Lat_n - Lat_l\right)^2 + \left(Long_n - Long_l\right)^2}{b^2} \right) \tag{5}$$

This is simply an exponential function of minus half of squared Euclidean distance of individual *n*'s location from location *l* divided by the square of the bandwidth parameter. If a respondent lives exactly in location l – this weight is equal to 1.[1] The use of this weight implies the clustering of similar values because observations near to location l have a larger bearing on the local model's log-likelihood compared to observations that are further away. The bandwidth parameter therefore determines what "further away" means. If the bandwidth is low, then practically only the observations in very close proximity of given location influence the local model. Specifically, when $b \to 0$ each local model is estimated using observations only from the given location. Analogously, when bandwidth is high, all local models will have similar parameter estimates, with $b \to \infty$ leading to a simple MNL model for the whole sample.

It is worth noting, that the choice of bandwidth may have a greater impact on the results than the choice of a specific weighting scheme (Fosgerau, 2007). There are several methods for choosing the bandwidth parameter available in the literature, with no apparent dominant approach. We tested three approaches, namely: using the corrected Akaike Information Criterion (AIC, Dekker, Koster and Brouwer, 2014), taking the lowest bandwidth for which all local models converge (Dekker, Koster and Brouwer, 2014), and using leave-one-individual-out cross-validation criterion (Fotheringham, Brunsdon and Charlton, 2003). To evaluate these, we used simulated data which utilized the designs utilized in our study. The results indicated that the available methods led to either under or over-smoothing and were unsatisfactory – a conclusion also voiced by Koster and Koster (2015). We therefore decided to use the 'eye-balling' approach they propose. In this approach, a researcher chooses the lowest bandwidth for which the model estimates satisfy a set of *a priori* specified conditions (e.g., achieving identification of all the models or avoiding extreme estimates). Pagan and Ullah (1999) recommend using this approach when the number of bandwidth parameters is not greater than 2, which is the case in our analysis. We decided that all

[1] For robustness check, we also tried different weighting functions, such as the spatially varying kernel (Fotheringham, Brunsdon and Charlton, 2003): $\lambda\left(Lat_n, Long_n, b, l\right) = \exp\left(-\frac{R_{n,l}}{b}\right)$, where $R_{n,l}$ is the rank of the *n-th* location from *l-th* location in terms of the distance *n* is from *l*. The results were not much different from the Gaussian kernel.

WTP estimates should lie in interval [-100, 100] EUR, for results to be reliable. Bandwidths that result in WTP estimates outside of this range can be considered as inappropriate.

Sample size

There is a concern regarding the size of sample needed to calculate a local model with reliable parameter estimates. Generally, the literature provides little guidance in this regard. Sample sizes and the number of local models vary greatly depending on the application. In the cases where secondary survey data are used, such as in the case of house prices (Cho, Poudyal and Roberts, 2008; Saphores and Li, 2012), school performance (Fotheringham, Charlton and Brunsdon, 2001) or land use (Wang, Kockelman and Wang (2011), the number of observations is typically high, ranging from around 3,700 to 50,000. Although, sometimes, for each observation there is estimated a separate local model. Applications using stated preference methods usually make use of much smaller datasets. For example, Fosgerau (2007) used data from 2000 respondents with 8 choice tasks per person and estimate 441 local models. Börjesson, Fosgerau and Algers (2012) estimated the local models using responses from 1317 individuals. Koster and Koster (2015) used a dataset of 487 individuals, and reported a local model for each. In this respect, our sample does not seem to be "too small", especially when considering the number of individuals per location. Nevertheless, as noted by one of our reviewers, for the GWMNL model the distribution of the individuals across the space maybe a bigger issue than the sample size. When there are locations with a low number of individuals, which are far away from any other individuals, the bandwidth needs to increase to provide any meaningful estimates (the bias-variance trade-off). Also, the locations with very high number of individuals may influence estimates of other local models unproportionally. Unfortunately, for now, the effect of the sampling on spatial distribution of WTP is not well researched, and it is not clear how it may affect the results.

The Location specific mixed logit model

The baseline for the comparison of the performance of GWMNL approach is provided by the location-specific conditional distributions retrieved from the mixed logit model (Czajkowski et al., forthcoming) which can be estimated in WTP-space. In this model, respondent *n*'s utility from choosing alternative *i* in the *j*-th choice task is given by:

$$U_{ijn} = \beta_l^{\text{cost}} \left(\boldsymbol{\alpha}_l' \mathbf{X}_{ijn}^{\text{non-cost}} - X_{ijn}^{\text{cost}} \right) + \varepsilon_{ijn} \ . \tag{6}$$

We assume that each location *l* has a separate, independent set of parameters and therefore, we assume that all individuals within given location have homogeneous preferences. We prefer this specification over usual, aspatial individual-specific one, because it is more comparable with the GWMNL approach. The usual, individual-specific MXL takes into account different sources of heterogeneity, while the GWMNL accounts for the spatial heterogeneity only.

Location-specific parameters are not directly observed, but it is possible to estimate their values implied by each respondents' choices conditional on the population-level estimates of parameter distributions (Bayesian posterior means) using the Bayes theorem:

$$E\left(\boldsymbol{\alpha}_l \mid \mathbf{y}_l, \mathbf{X}_l, \theta\right) = \int \boldsymbol{\alpha}_l \frac{p\left(\mathbf{y}_l \mid \mathbf{X}_l, \theta, \boldsymbol{\alpha}_l, \beta_l^{\text{cost}}\right) f\left(\boldsymbol{\alpha}_l, \beta_l^{\text{cost}} \mid \theta\right)}{p\left(\mathbf{y}_l \mid \mathbf{X}_l, \theta\right)} d\left(\boldsymbol{\alpha}_l, \beta_l^{\text{cost}}\right), \tag{7}$$

where $p\left(\mathbf{y}_l \mid \mathbf{X}_l, \theta, \boldsymbol{\alpha}_l, \beta_l^{\text{cost}}\right)$ is the likelihood of all individuals from location *l* making the observed choices conditional on the values of random parameters, $p\left(\mathbf{y}_l \mid \mathbf{X}_l, \theta\right)$ is the same likelihood but unconditional (so it is likelihood function for MXL) and $f\left(\boldsymbol{\alpha}_l, \beta_l^{\text{cost}} \mid \theta\right)$ is the assumed pdf function of random parameters (normal distribution for all attributes except for the cost, which was assumed to be log-normally distributed). For more details about this approach see Czajkowski et al. (forthcoming).

Note, that contrary to the MXL model, in the GWMNL there is no need to specify a distribution from which the parameters are drawn. It is also important to note that in this specification the MXL model parameters associated with different locations are independent. Spatial dependence is, therefore, accommodated indirectly as it arises from the calculation of conditional expected values of random parameters.

Data

The original survey was conducted in 2010 on a representative sample[2] of 1001 Polish adults. The main objective of the survey was estimate public preferences over management options for the national forest area (rather than specific local forests). The attributes used to describe these management options were (1) passive protection of the most ecologically valuable forests,[3] (2) reducing the amount of litter (garbage, rubbish) in forests through tougher law enforcement and by increasing forest cleaning services and (3) increasing the level of recreational infrastructure, such as improved signposting of forest trails. The dataset used in this study was also exploited in in Czajkowski et al. (2014) and Czajkowski, Giergiczny and Greene (2014), where the attributes, experimental design and sampling strategy are described in detail.

Information on forest characteristics used in this study was obtained from two different sources. Firstly, the CORINE Land Cover (CLC) dataset was used. This project is coordinated by the European Environment Agency with the objective of collecting high resolution data for the whole continent.[4] CLC databases contain area data for objects with a minimum area of 5 ha and a width of more than 100 meters. The second source of information used was the Polish Information System of State Forests. This contains very precise data about the characteristics of forests in Poland. The data from these sources was aggregated to 10x10 km squares.[5] In total, 3,307 such squares cover the

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[2] We hired a professional polling agency that collected the questionnaires using high-quality, face-to-face computer-assisted surveying techniques. A multi-stage sampling strategy was employed, in which communities were randomly selected to represent different community types, and then within each of the selected communities. A starting point address was randomly selected and then a set of addresses was chosen using the random route method. Finally, a random selection of an adult household member was employed.

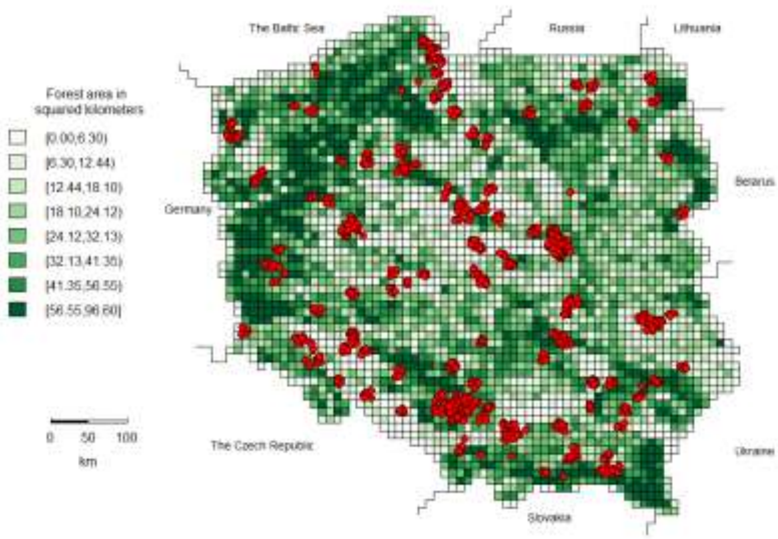
[3] By passive (as opposed to active) protection of the forest, we mean leaving the forest ecosystem without any human intervention, even if this results in (natural) changes in ecosystems. It was highlighted that passive protection does not preclude recreational use.

[4] See http://www.eea.europa.eu/publications/COR0-landcover for further information on the CORINE program.

[5] We also tested aggregating the 50x50 km resolution which provided equivalent results, although model fits were

area of Poland. Figure 2 presents a map with a distribution of DCE study respondents. The GIS data were associated with particular respondents using their ZIP-codes identifying their place of residence. For every respondent, the explanatory variables were calculated as weighted averages of forest characteristics in the 10x10 km area common with respondents' ZIP area code. The GIS variables used in this study are described in Table 1.

Figure 2. Respondents and forest area spatial distribution (red dots denote respondents' place of living)[6]



inferior.

[6] As some respondents reported the same ZIP-codes we jittered all of them with uniform random variable on [-5,5] x [-5,5] km square. This also allow us to compute spatial weights matrix.

Table 1. GIS variables used to characterize the locations in which respondents' lived

Variable name	Description	Source	Mean	St. Dev.
Area of coniferous forests	Sum of areas of all coniferous forests [km^2]	Corine Land Cover	11.3202	13.3060
Area of deciduous forests	Sum of areas of all deciduous forests [km^2]	Corine Land Cover	4.2290	3.9805
Area of mixed forests	Sum of areas of all mixed forests [km^2]	Corine Land Cover	6.5767	6.1084
Average Euclidean distance to forest	It is average distance from any point in 10x10 km square to the nearest forest	Corine Land Cover	1.3075	0.8921
Area of forests with age > 120	Sum of areas of all forests older than 120 years [km^2]	Information System of State Forests	0.9586	1.3336
Area of forests with the number of species > 6	Sum of areas of all forests with the number of tree species greater than 6 [km^2]	Information System of State Forests	5.9285	7.1911
Built-up area	Built-up area [km^2]	Corine Land Cover	19.5532	19.3520

The input for our geographically weighted models was the spatial data set of the respondents, where the location was given as coordinates of ZIP-codes, and the locations were linked to responses and environmental variables. Prior to running the GWMNL model, the original WGS1984 coordinates were projected using the ETRS_1989_Poland_CS92 coordinate system and the projected coordinates were normalized.

The sample used in our study, 1001 individuals with 26 choice tasks per respondent, is sufficient for estimation of 253 local models. Note that number of individuals vary between locations, with some locations having only one individual, and some having more than 10 individuals. This result in unbalanced panel, which may make estimates for locations with small number of individuals imprecise. Specifically, in the case of MXL, when number of individuals in the given location is small, the Bayesian posterior will be dominated by the chosen mixing distribution. In the case of GWMNL, the estimation of local models involves a tradeoff of bias and variance of estimates (Fotheringham, Brunsdon and Charlton, 2003). Nevertheless, if parameters values change continuously throughout space the properly chosen bandwidth should provide reliable estimates for local models.

Results

Following the approach outlined earlier, we estimated the GWMNL models for each of the 253 distinct locations in which our 1,001 respondents were located.[7] Table 2 presents the summary statistics of the estimated parameters for this model, which are compared with results from the MNL and the location-specific MXL models.[8] For the GWMNL model, we present means and standard deviations of parameter estimates across 253 local models, which allows for straightforward comparison with parameters from MXL model.

Table 2. Results of the MNL, location specific MXL and GWMNL models (standard errors in brackets, coefficients in WTP-space, in EUR per year[9]).

Variable	MNL model	Location specific MXL model		GWMNL	
		Mean	Std. Dev.	Mean	Std. Dev.
	coef. (st. err.)	coef. (st. err.)	coef. (st. err.)	coef. (st. err.)	coef. (st. err.)
NAT_1	14.8307***	11.7961***	7.6114***	15.7107***	6.8786***
(passive protection of most valuable forests – partial improvement)	(0.5673)	(0.4288)	(0.4559)	(0.1258)	(0.1701)
NAT_2	21.8207***	16.8630***	12.1756***	23.0767***	10.0173***
(passive protection of most valuable forests – substantial improvement)	(0.7248)	(0.6129)	(0.6531)	(0.1826)	(0.2575)
TRA_1	26.6697***	17.4477***	8.3347***	28.3018***	11.0293***
(the amount of litter in forests – partial improvement)	(0.8298)	(0.6066)	(0.4433)	(0.2001)	(0.2316)
TRA_2	35.6782***	25.2329***	14.1371***	37.8590***	14.7594***
(the amount of litter in forests – substantial improvement)	(1.0664)	(0.9080)	(0.7508)	(0.2721)	(0.3624)

[7] In the estimation, we used the bandwidth parameter of 0.475 which was the lowest value to satisfy our a priori (albeit arbitrarily) specified condition that all models converge and in no location the estimated WTP is larger than 100 EUR. See section 3.1 for discussion and Appendix A for the robustness analysis of this assumption.

[8] Standard errors for the GWMNL model estimates were Monte-Carlo simulated using 10,000 repetitions, in which parameters of every locally estimated model were assumed to follow multivariate normal distribution.

[9] At 1 PLN ≈ 0.23 EUR ≈ 0.25 USD.

INF$_1$	12.1400***	8.2641***	4.5826***	12.7121***	5.1219***
(tourist infrastructure – partial improvement)	(0.5269)	(0.3997)	(0.3251)	(0.0915)	(0.1003)
INF$_2$	19.5598***	12.1145***	6.5138***	20.6085***	8.2931***
(tourist infrastructure – substantial improvement)	(0.6553)	(0.5044)	(0.3723)	(0.1388)	(0.1543)
SQ	37.2443***	-3.2461***	43.2764***	39.3765***	26.2943***
(alternative specific constant for the no-choice alternative)	(1.4032)	(0.7457)	(2.1355)	(0.3866)	(0.4566)
COST	0.0538***	-2.2472***	0.7066***	0.0575***	0.0240***
(annual cost – tax increase)	(0.0014)	(0.0400)	(0.0245)	(0.0004)	(0.0005)
Model characteristics					
Log-likelihood (constant only)	-36,045.3765	-36,045.3765		-36,045.3765	
Log-likelihood	-29,708.2771	-22,632.3017		-28,555.9663[10]	
Ben-Akiva Lerman's pseudo-R^2	0.3282	0.4626		0.3550[14]	
McFadden's pseudo-R^2	0.3308	0.3721			
AIC/*n*	2.2836	1.7426		2.1950[14]	
n (observations)	26,026	26,026		26,026	
k (parameters)	8	44			

*** p-value < 1%, ** p-value in [1%,5%), * p-value in [5%, 10%)

As our model was estimated in WTP-space, parameters for all attributes can be interpreted directly as willingness to pay. Qualitative results mimic those found in Czajkowski et al. (forthcoming), namely that on average the individuals are willing to pay the most for reducing of amount of litter and the least for improvements in infrastructure.

The comparison of WTP characteristics between the models reveals that means of the GWMNL estimates are very close to MNL estimates. In contrast, for the location-specific MXL the mean WTP values are significantly lower. The biggest difference is observed for the mean estimates of alternative specific constant parameter (SQ) which has a reversed sign. Finally, we note that the standard deviations are of similar magnitude in both approaches (except for *SQ* which has a higher standard deviation in the location-specific MXL model).

[10] For GWMNL these are mean values across 253 local models

There are, at least, three possible reasons for why we observe significant changes in the mean WTP values. Firstly, one can expect that not allowing for spatial correlation in the specification of the MXL model may lead to biased estimates. Secondly, the assumption of the MNL model form of local models in GWMNL may not be justified, because the error terms could in reality be correlated across alternatives. Lastly, and crucially, it may be driven by the distributional assumptions of the MXL model. While the MXL model assumes that the cost*scale parameter is log-normally distributed and that the marginal WTP distributions are all normally distributed, the GWMNL model is a semi-parametric approach and thus makes no such assumptions.

In order to compare the relative fit to the data provided by each of the three models (GWMNL, MNL and location -specific MXL models) we propose to use the Ben-Akiva-Lerman's pseudo-R^2 (Ben-Akiva and Lerman, 1985). This is a measure of predicted probabilities of choosing the alternatives which were actually chosen by respondents – an intuitive way of illustrating how well a model predicts the observed choices. We adapt this measure to the panel character of our data – because each respondent or each location was associated with *n* choice tasks, the joint probability of the observed series of *n* choices is normalized by taking its *n*-th root. Mean probabilities are presented in Table 2 (Ben-Akiva-Lerman's pseudo-R^2), while their spatial distribution is illustrated in Figure 3. The pattern that emerges is clear – although the GWMNL approach provides a better fit than the MNL model, it is worse than the location-specific MXL model. Apparently the ability to generically account for the unobserved preference heterogeneity offers more of an improvement in fit than explicitly accounting for spatial correlations in the MNL model. However, we note that the predicted probabilities are highly correlated – the regions in which respondents' choices are relatively better or worse predicted are unchanged across the four models. This observation is further illustrated with the results provided in Table 3 – the correlation coefficients between location specific choice probabilities predicted by different models. Indeed, the predictions from GWMNL are more correlated with MNL, than with MXL.

Figure 3. Model-specific predicted probabilities of the observed choices (Ben-Akiva-Lerman's pseudo-R^2)

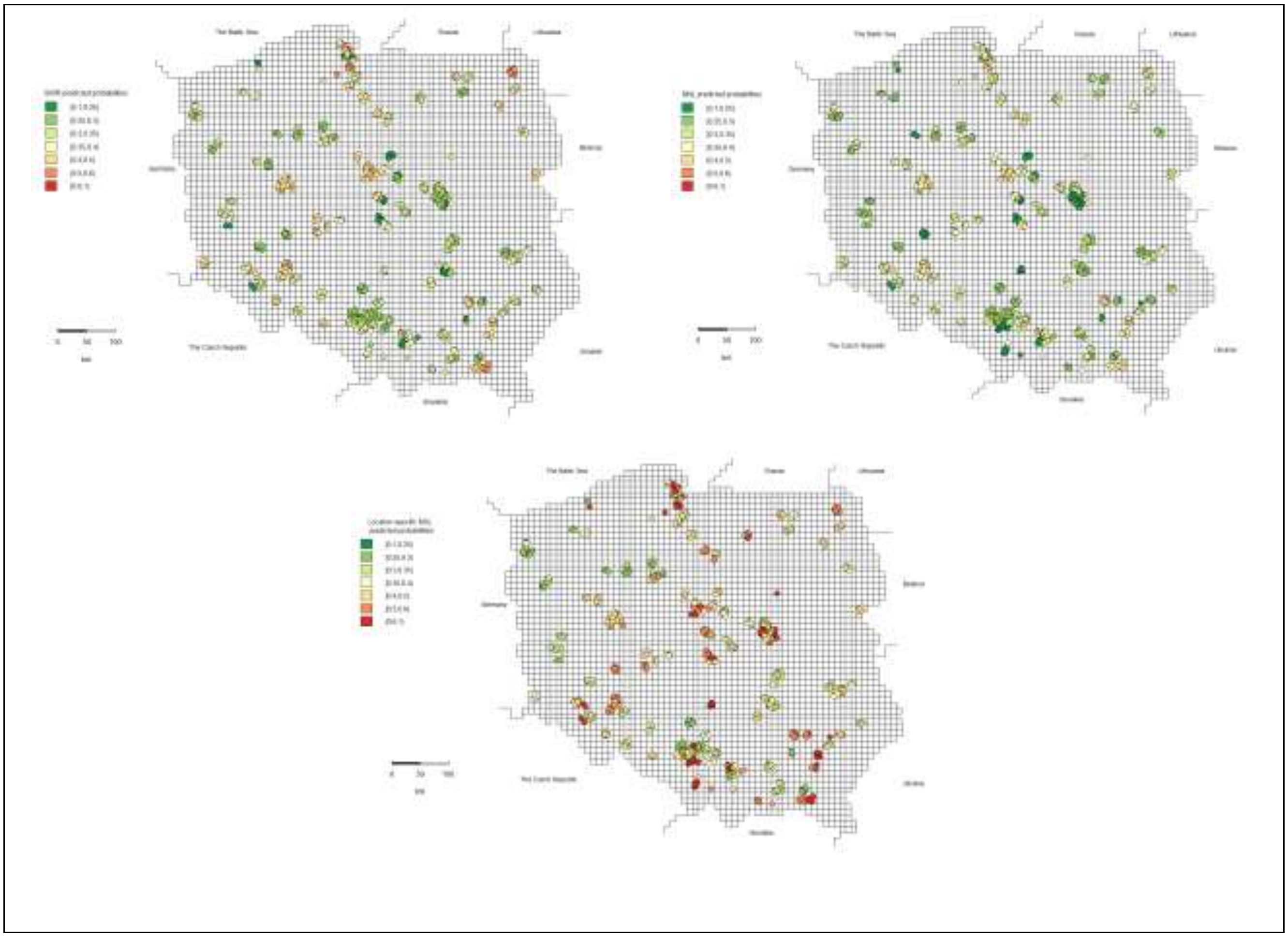


Table 3. Correlation coefficients of model-specific predicted probabilities of the observed choices (Ben-Akiva-Lerman's pseudo-R^2)

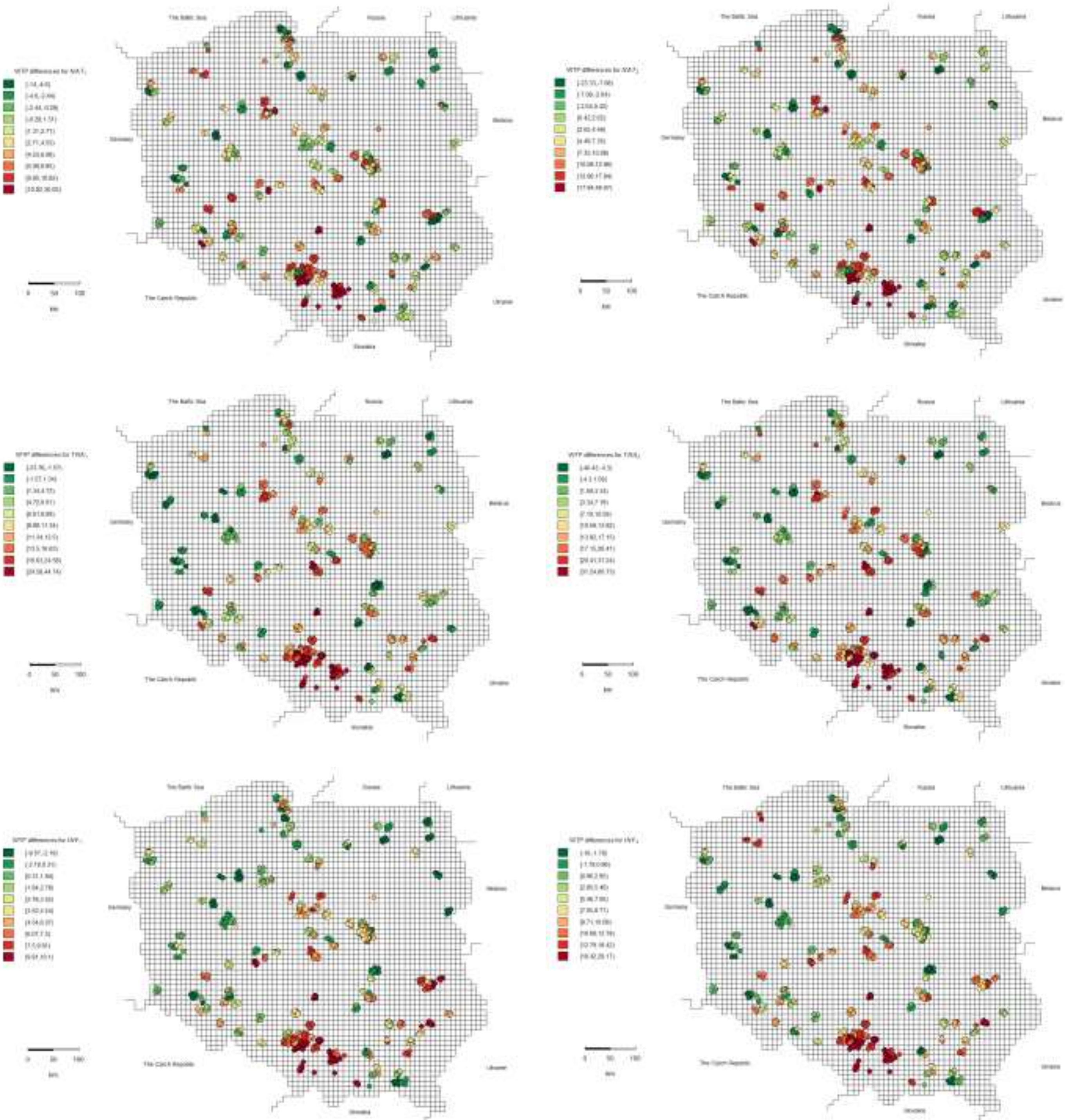
	GWMNL (*b*=0.475)	MNL	Location specific MXL model
GWMNL (*b*=0.475)	1.0000	0.7782	0.4110
MNL	0.7782	1.0000	0.2313
Location specific MXL model	0.4110	0.2313	1.0000

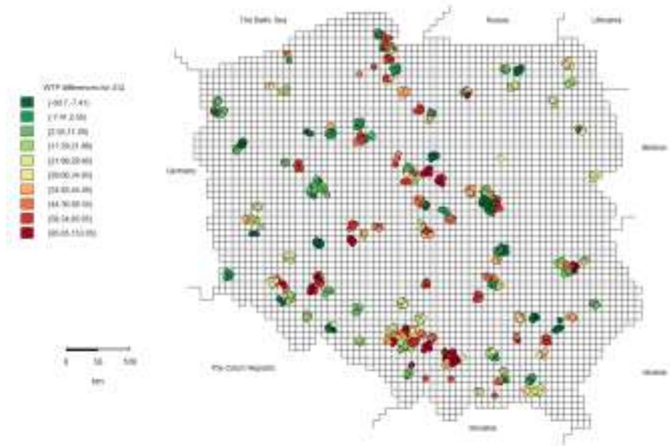
In order to analyze the discrepancies between the geographically weighted and the traditional two-step approach further we can compare the differences between WTP estimates for every location presented on map of Poland. This is done in the 7 panels of Figure 4. In these panels positive values depict locations where GWMNL (b=0.475) estimates are higher (red) and negative values depict locations where conditional expected values from location-specific MXL are higher (green). Distributions of these differences are not symmetric with respect to 0 (as every interval consists of 10% of the sample). For all attributes, more than 80% of observations have positive values (higher values of WTP from GWMNL).

Graphical analysis reveals several spatial patterns of between-estimate differences which are consistent across all attributes. First of all, the largest differences can be observed in the central-south part of Poland near Cracow and Katowice cities, where GWMNL approach leads to much higher estimates of WTP. Secondly, in the west and north-east parts of Poland the differences seem to be much lower, sometimes negative. In the other parts of the country there is no clear spatial pattern, although it seems that also in the central part the differences are rather low (but positive). The fact, that some spatial patterns can be observed is an indication that these the two approaches recover different spatial dependencies of preferences. As GWMNL is designed to recover such spatial dependencies we can expect it to work better in this regard.

In order to investigate any systematic dependencies in these differences we estimated simple linear regressions in which their absolute values are explained by GIS variables and the number of observations per location. The full results are available in Appendix B. In short, we found that for locations with higher number of observations differences in WTP are significantly lower. This may indicate, that with more homogeneous sampling (with multiple observations per location) the two methods become more similar. What is more, we found that the differences are lower in areas with high coverage of very old forests, but are higher in built-up areas and areas with high coverage of forests with more than 6 tree species.

Figure 4. Spatial distribution of differences between WTP estimates from GWMNL and conditional expected values from location-specific MXL.





Lastly, it is possible to perform a decomposition of the estimated WTP using GIS variables, similar to Czajkowski et al. (forthcoming). To this end, seven regressions were estimated in which WTP were explained by the same GIS variables as in Czajkowski et al. (forthcoming). The results from linear regression model on the GWMNL (*b*=0.475) results are given in Table 4, whereas the spatial lag models based on the conditional expected values of random parameters from location-specific MXL are presented in Table 5.[11] In all cases we decided to use only GIS variables and omit socio-demographic variables, since these were insignificant in most cases for the GWMNL and location-specific MXL approaches. Testing their joint significance we found that at 5% significance level socio-demographic variables are significant only in NAT_1 and NAT_2 equations, and not significant in any equation at 1% significance level. We think that these results may be caused partly by the fact that we needed to average socio-demographic variables over individuals in the same location, as in Czajkowski et al. (forthcoming), where this relationship was analyzed on the individual level, socio-demographic variables were more significant.

[11] Note that in current analysis we used Ordinary Least Square instead of spatial lag model. It was not possible to estimate spatial lag model on WTP estimated from GWMNL as from definition these are highly spatially autocorrelated and therefore coefficient ρ (which is coefficient for spatial lag term) was almost equal to 1 and no other variable would then occur significant.

Looking firstly at the results based on the GWMNL results, we find that most of GIS variables are highly significant. We can compare these estimates with results in Table 5 in order to investigate structural differences in spatial heterogeneity in WTP estimates between the GWMNL and Bayesian posterior means from location-specific MXL. Greyed out cells of Table 4 indicate coefficients which have a different sign than equivalent coefficients in Table 5. This issue is the most prominent in regression for the *SQ*, where 3 variables have different signs, although they are all insignificant in this case. This problem also occurs, for almost every attribute, with "*Area of forests with age > 120*" variable. In case of location-specific MXL, this variable has a positive (although insignificant) coefficient for most attributes. What is also interesting is that in the current analysis variables "*Built-up area*" and "*Area of forests with no. of species > 6*" were significant in almost all cases. This differs to what we discovered when using the conditional expected values of random parameters from the MXL model where these variables were insignificant in all cases.

Table 4. Results of regressions in which WTP estimates from GWMNL are explained by GIS variables

	SQ (alternative specific constant for the no-choice alternative)	NAT_1 (passive protection of most valuable forests – partial improvement)	NAT_2 (passive protection of most valuable forests – substantial improvement)	TRA_1 (the amount of litter in forests – partial improvement)	TRA_2 (the amount of litter in forests – substantial improvement)	INF_1 (tourist infrastructure – partial improvement)	INF_2 (tourist infrastructure – substantial improvement)
Constant	34.7688*** (5.7861)	17.6132*** (1.5842)	27.0083*** (2.4027)	30.8844*** (2.4394)	44.8497*** (3.4203)	11.8696*** (1.0303)	22.0946*** (1.8038)
Area of coniferous forests	-0.1544 (0.1362)	-0.0727* (0.0373)	-0.1088* (0.0566)	-0.0732 (0.0574)	-0.1519* (0.0805)	0.0239 (0.0243)	-0.0449 (0.0425)
Area of deciduous forests	1.0730** (0.4567)	-0.1207 (0.1251)	-0.3464* (0.1897)	-0.0479 (0.1926)	-0.3411 (0.2700)	0.2376*** (0.0813)	0.2164 (0.1424)
Area of mixed forests	-0.1680 (0.3356)	-0.2419*** (0.0919)	-0.3022** (0.1393)	-0.2930** (0.1415)	-0.4331** (0.1984)	-0.0364 (0.0598)	-0.2270** (0.1046)
Area of forests with age >120	-7.0385*** (1.4597)	-0.4937 (0.3996)	-0.5343 (0.6061)	-1.3759** (0.6154)	-1.0958 (0.8628)	-1.4039*** (0.2599)	-2.0912*** (0.4550)
Average Euclidean distance to a forest	-1.7794 (2.3522)	-1.1623* (0.6440)	-1.7118* (0.9768)	-2.3111** (0.9917)	-3.8154*** (1.3904)	0.0347 (0.4189)	-1.1040 (0.7333)
Built-up area	0.2859*** (0.0793)	0.0813*** (0.0217)	0.1123*** (0.0329)	0.1454*** (0.0334)	0.1703*** (0.0469)	0.0129 (0.0141)	0.0405 (0.0247)
Area of forests with no. of species > 6	1.0447***	0.2774***	0.3147**	0.3567**	0.4133**	0.1161*	0.3829***

	(0.3331)	(0.0912)	(0.1383)	(0.1405)	(0.1969)	(0.0593)	(0.1039)
Model characteristics							
R^2	0.2195	0.1215	0.0980	0.1293	0.0925	0.1556	0.1648
n (observations)	253	253	253	253	253	253	253
k (parameters)	8	8	8	8	8	8	8

*** p-value < 1%, ** p-value in [1%,5%), * p-value in [5%, 10%)

Table 5. Results of spatial lag models in which Bayesian posterior means from MXL model are explained by GIS variables.

	SQ (alternative specific constant for the no-choice alternative)	*NAT_1* (passive protection of most valuable forests – partial improvement)	*NAT_2* (passive protection of most valuable forests – substantial improvement)	*TRA_1* (the amount of litter in forests – partial improvement)	*TRA_2* (the amount of litter in forests – substantial improvement)	*INF_1* (tourist infrastructure – partial improvement)	*INF_2* (tourist infrastructure – substantial improvement)
Location-specific MXL							
Constant	-35.0845*** [9.0012]	15.2120*** [1.9167]	23.2420*** [2.9933]	16.2849*** [2.1964]	26.6299*** [3.5287]	5.9459*** [1.0342]	8.9798*** [1.4828]
Area of coniferous forests	0.4807** [0.2108]	-0.0828** [0.0371]	-0.1442** [0.0595]	-0.0674* [0.0402]	-0.1537** [0.0668]	0.0054 [0.0202]	-0.0129 [0.0284]
Area of deciduous forests	2.5479*** [0.6502]	-0.3785*** [0.1139]	-0.6469*** [0.1829]	-0.1931 [0.1226]	-0.5320*** [0.2043]	0.0471 [0.0616]	0.0096 [0.0867]
Area of mixed forests	0.7688* [0.4489]	-0.1880** [0.0791]	-0.3133** [0.1270]	-0.2060** [0.0859]	-0.3404** [0.1425]	-0.0634 [0.0430]	-0.1022* [0.0607]
Area of forests with age >120	-0.6381 [2.2125]	0.6013 [0.3907]	0.9906 [0.6268]	0.4653 [0.4225]	0.9354 [0.7025]	-0.0776 [0.2117]	0.0971 [0.2983]
Average Euclidean distance to a forest	10.8442*** [3.3104]	-1.6825*** [0.5811]	-2.8926*** [0.9328]	-1.6013** [0.6309]	-3.2686*** [1.0499]	-0.2967 [0.3153]	-0.6871 [0.4454]
ρ	0.2555*** [0.0723]	0.1810** [0.0760]	0.1824** [0.0758]	0.3397*** [0.0681]	0.3325*** [0.0682]	0.3700*** [0.0664]	0.4090*** [0.0637]
Model characteristics							
Log Likelihood	-1255.8570	-814.7967	-934.2825	-838.5166	-966.3454	-665.4564	-753.4436
AIC/n	10.0246	6.5194	7.4643	6.7622	7.7718	5.4062	6.1279
n (observations)	253	253	253	253	253	253	253
k (parameters)	8	8	8	8	8	8	8

*** p-value < 1%, ** p-value in [1%,5%), * p-value in [5%, 10%)

Overall, the results indicate that there are significant discrepancies with regard to spatial patterns recovered with the two methods. Differences in the signs and significance of coefficients for GIS variables demonstrate that the WTP distributions differ in structure between these two approaches. As the GWMNL model explicitly deals with spatial heterogeneity (rather than trying to recover it indirectly post estimation) it could be considered more reliable. It is also important to note that in all models using the GWMNL estimates the R^2 in all models is very low, which suggest that the GIS variables we used explain only a small fraction of the observed variance. Therefore, assuming that the estimated values obtained from the GWMNL models are the true values, most of the heterogeneity in WTP is caused by some other factors, which we do not account for. This may partly be due to the spatial distribution of forest characteristics in Poland.

In some cases the differences between forests which lie next to each other are large, and therefore significant variance in their values may occur even on a local level. Because of that, our model may not be able to recover relationship between these factors and preference heterogeneity correctly, as we do not have sufficiently detailed data to model this local variation. It is possible that the GWMNL approach would perform better in the case of preferences for environmental goods which change more gradually.

Discussion and conclusions

In this paper we investigate two alternative methods for addressing spatial patterns in willingness to pay for changes to an environmental good. We argued that knowledge of how willingness to pay for a specific environmental change varies across space is useful from a policy and management perspective. Knowing the spatial pattern of values can help resource managers target investments in site quality, or in new forests, as investments can be directed at locations where they are most valued. It also enables a higher-resolution identification of the gainers and losers from changes in resource management, since now the location of individuals who gain by a given amount from a policy can be mapped. An example of how important this might be is provided by Hynes et al (2010) using contingent valuation survey data for Ireland. They found that allowing for spatial differences in the characteristics of individuals (in their case, farmers) via a micro-simulation approach resulted in significantly different estimates of willingness to pay for biodiversity conservation at the regional level, and thus significantly different measures of aggregate benefits, compared to an aggregation method which did not take into account spatial variation in the characteristics of beneficiaries.

Given the costs of original survey work, the ability to produce such maps cost-effectively is highly desirable so long as results are sufficiently robust. The case study used to generate the data with which the two alternative methods are tested concerns the management of forests in Poland. We introduced a novel method of geographically weighted discrete choice models to account for spatial heterogeneity of model parameters, and compared this to a standard “two-step” approach using the MXL model and posterior Bayesian means of random parameters (Czajkowski et al., forthcoming). The comparison focused on the consequences for estimates of willingness to pay, as this is typically the focus in environmental economics. Our analysis revealed significant differences in the estimates of WTP between the two methods. Specifically, for all forest attributes, mean WTP was much higher when obtained using GWMNL. We also found some important structural differences – several land cover variables appeared to have a reversed effect on WTP when the models are compared.

We note that both methods have shortcomings. MXL assumes that random parameters are drawn from spatially independent distributions and relies heavily on distributional assumptions. Any spatial correlations that are observed are obtained from posterior Bayesian means, and they are, obviously, conditional on these assumptions. On the other hand, GWMNL ignores other (non-spatial) sources of preference heterogeneity, such as variations in income, which other research has shown to matter. This shortcoming of the GWMNL model could be addressed by using a more complicated weighting function which accounts for socio-demographic characteristics. However, this may require the use of multiple bandwidth parameters. We tried to incorporate heterogeneity with respect to socio-demographic characteristics by using a second bandwidth parameter, but the results were not satisfactory, particularly when using the eye-balling technique to determine the optimal bandwidth value. First of all, in such a setting there was no unique ‘lower’ bandwidth for which our criterion was fulfilled, e.g. in case of having criterion of all WTP being below 100 EUR, there could exist several pairs of bandwidths for which all WTP values are below this chosen level, such that an increase in any of bandwidths would lead to exceeding this level. Researchers would therefore need some additional criterion to choose the preferred model. Second, the number of models that one needs to estimate increases very quickly with the number of bandwidth parameters, e.g. if for a single bandwidth researcher wants to evaluate 20 different models, then for two bandwidth parameters about 20x20=400 models need to be evaluated. Another possibility is to include unobserved heterogeneity in local models via estimation of latent class models instead of simple multinomial logits. Such approach was used by Koster and Koster (2015) (although not in the spatial context) and may be a preferable approach to GWMNL. This also introduces additional computational burdens, however.

In light of the above, it is difficult to conclude that either of the two methods presented here for the spatial modelling of willingness to pay is superior. Additional analysis of the reliability of Bayesian posterior means and their vulnerability to MXL assumptions is needed. To some extent, Hess (2010) approach this issue, but with no focus on welfare measures. Moreover, methods for choosing an appropriate bandwidth parameter in geographically weighted discrete choice models are currently under-developed. Many of the methods proposed are unsatisfactory and lead to poor results. This is especially important for more advanced kernels and with multiple bandwidth parameters, which would allow for spatial sources of heterogeneity. Lastly, more research on sampling design for such spatial models is needed, in terms of the implications for estimates of spatial relationships. We could expect that more homogenous geographic sampling would provide better results, although then the sample will no longer be representative.

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Appendix A

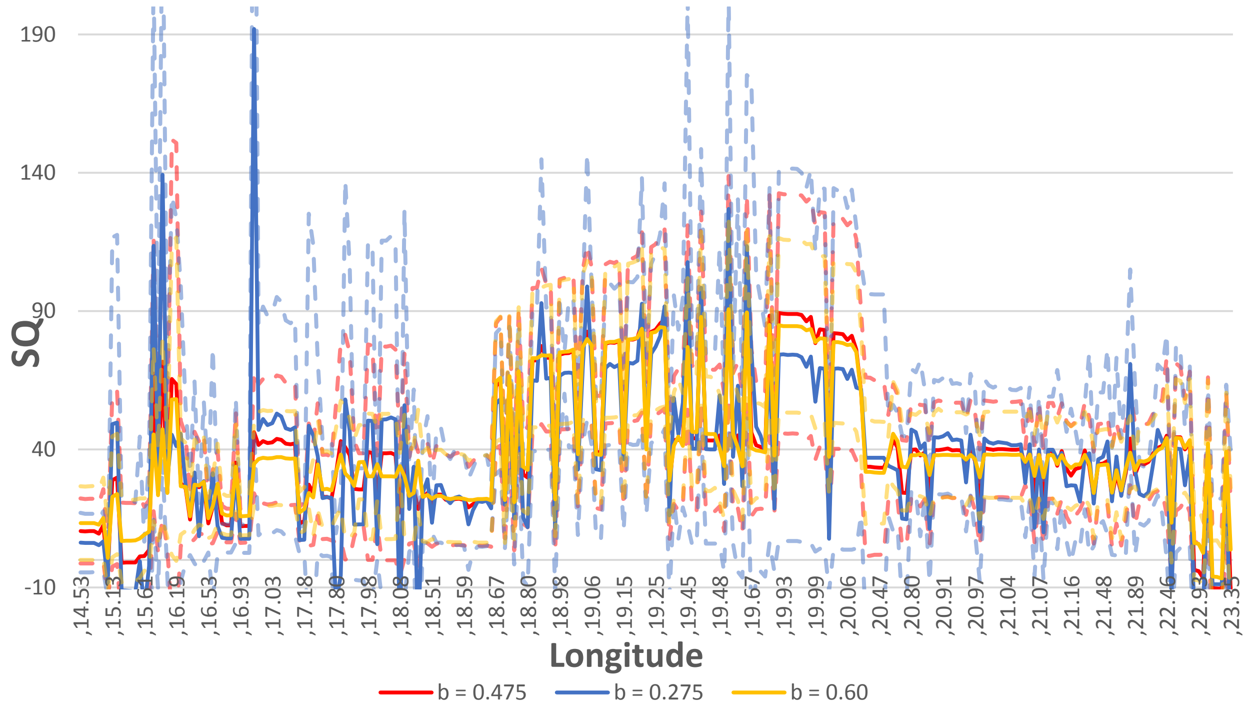
In this section we check robustness of our results by analyzing differences in estimates for 3 different values of bandwidth parameter: 0.275, 0.475 and 0.6. 0.475 is a value used throughout the paper, 0.275 is the lowest bandwidth value for which all WTP except SQ are below 100 EUR and 0.6 is the highest value we considered (as it is generally recommended to use lowest bandwidth value which fulfill chosen criteria). In Table A1. we provide characteristics of WTP for these values of bandwidth analogously as it was done in Table 2. We note that mean WTP are quite robust with respect to choice of a bandwidth. Although mean estimates for bandwidth values of 0.275 and 0.6 lie more than two standard errors from estimates for bandwidth = 0.475, they are fairly close to each other. Dispersion of WTP change significantly between different bandwidth values. To investigate how change in dispersion influence our results we conducted a graphical analysis presented in Figure A1. In every panel we plotted parameters estimates for chosen bandwidth values: 0.275 (blue lines), 0.475 (red lines) and 0.6 (yellow lines) with their 95% confidence intervals (dotted lines) against longitude. We see that, indeed increased dispersion for bandwidth of 0.275 leads to several 'peaks', with very wide confidence intervals, for every parameter. Because of that for lower bandwidth value many WTP estimates in local models occurred insignificant. Estimates for 0.6 bandwidth usually lies within confidence interval for estimates for bandwidth of 0.475. We therefore conclude that choosing bandwidth of 0.475 is justified as it allows to avoid implausible 'peaks' in WTP (especially for SQ) and insignificant estimates. We also do not see any reason to choose bandwidth above 0.475 as the plots does not reveal any particular under-smoothing when comparing lines for bandwidth of 0.475 with lines for bandwidth of 0.6.

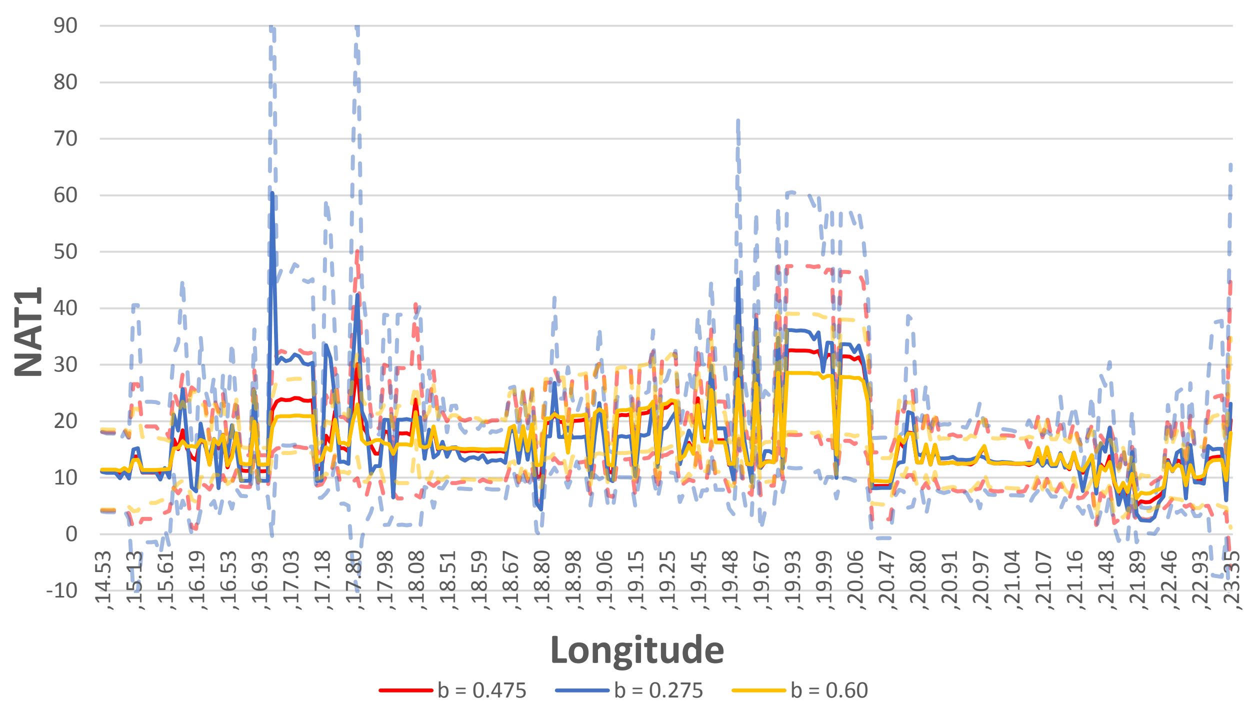
Table A1. Characteristics of distributions of estimated WTP from GWMNL model for different bandwidth values (stanrard errors in [] brackets, coefficients in WTP-space, in EUR per year)

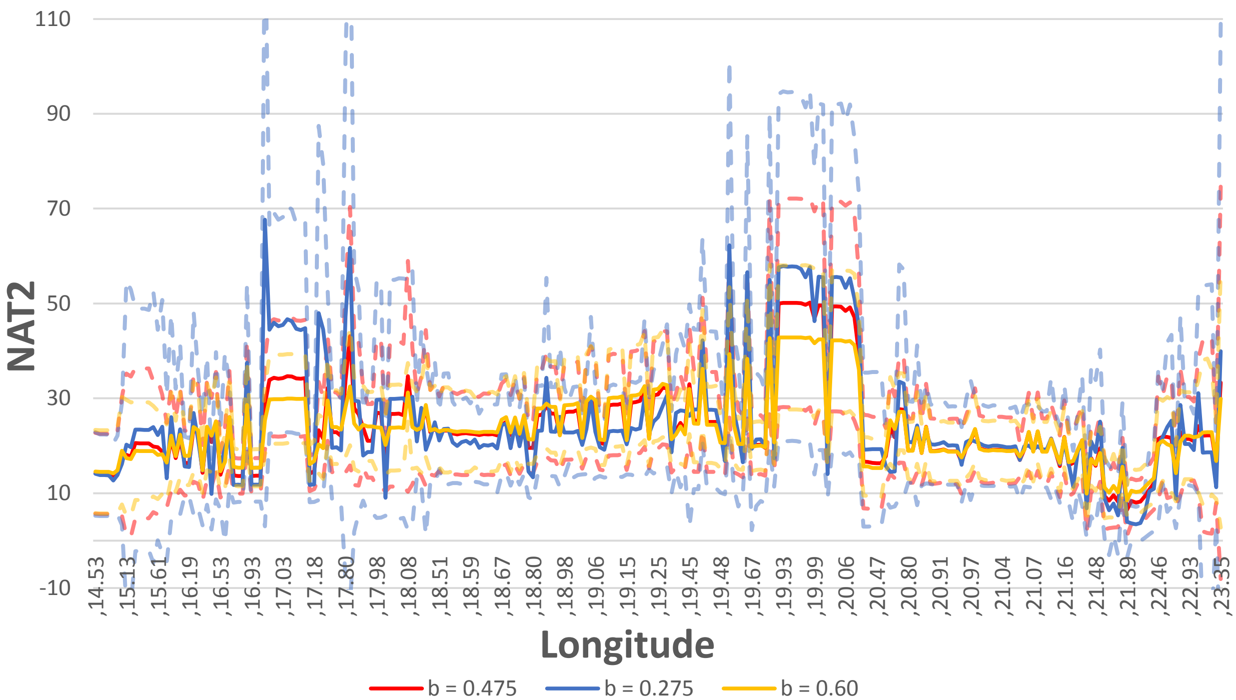
	Bandwidth = 0.275		Bandwidth = 0.475		Bandwidth = 0.6	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
NAT_1	16.4541***	10.9360***	15.7107***	6.8786***	15.5389***	5.7223***
(passive protection of most valuable forests – substantial improvement)	[0.2225]	[0.5033]	[0.1258]	[0.1701]	[0.0968]	[0.1138]
NAT_2	24.0868***	15.4706***	23.0767***	10.0173***	22.7602***	8.1253***
(passive protection of most valuable forests – partial improvement)	[0.3136]	[0.5758]	[0.1826]	[0.2575]	[0.1390]	[0.1682]
TRA_1	29.6563***	16.7661***	28.3018***	11.0293***	27.8463***	9.0786***
(the amount of litter in forests – partial improvement)	[0.3318]	[0.4383]	[0.2001]	[0.2316]	[0.1530]	[0.1704]
TRA_2	39.8062***	22.7725***	37.8590***	14.7594***	37.1348***	11.8575***
(the amount of litter in forests – substantial improvement)	[0.4591]	[0.6970]	[0.2721]	[0.3624]	[0.2041]	[0.2446]
INF_1	12.9375***	7.5310***	12.7121***	5.1219***	12.6410***	4.3811***
(tourist infrastructure – partial improvement)	[0.1469]	[0.1862]	[0.0915]	[0.1003]	[0.0736]	[0.0793]
INF_2	21.1835***	11.5530***	20.6085***	8.2931***	20.4056***	7.1172***
(tourist infrastructure – substantial improvement)	[0.2223]	[0.2611]	[0.1388]	[0.1543]	[0.1064]	[0.1127]
SQ	38.7161***	37.5901***	39.3765***	26.2943***	39.5860***	23.3231***
(alternative specific constant for the no-choice alternative)	[0.6308]	[1.1447]	[0.3866]	[0.4566]	[0.3046]	[0.3690]
COST	0.0626***	0.0403***	0.0575***	0.0240***	0.0561***	0.0182***
(annual cost – tax increase)	[0.0005]	[0.0008]	[0.0004]	[0.0005]	[0.0003]	[0.0003]

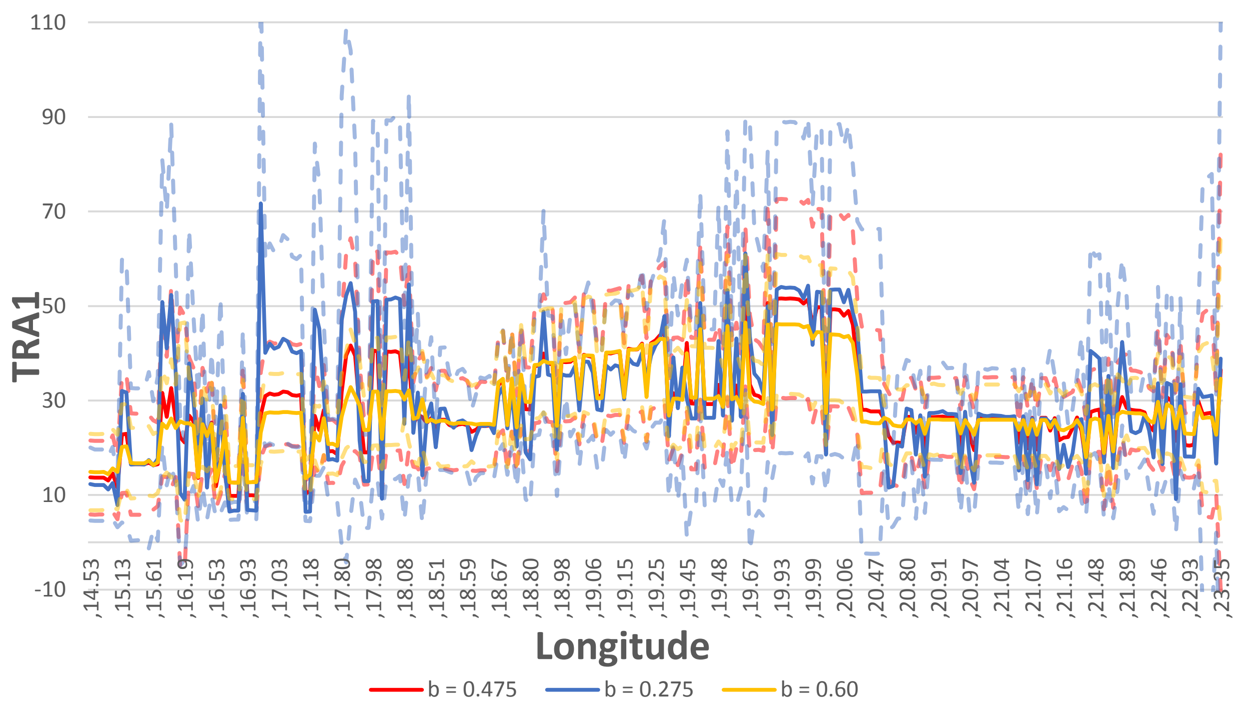
*** p-value < 1%, ** p-value in [1%,5%), * p-value in [5%, 10%)

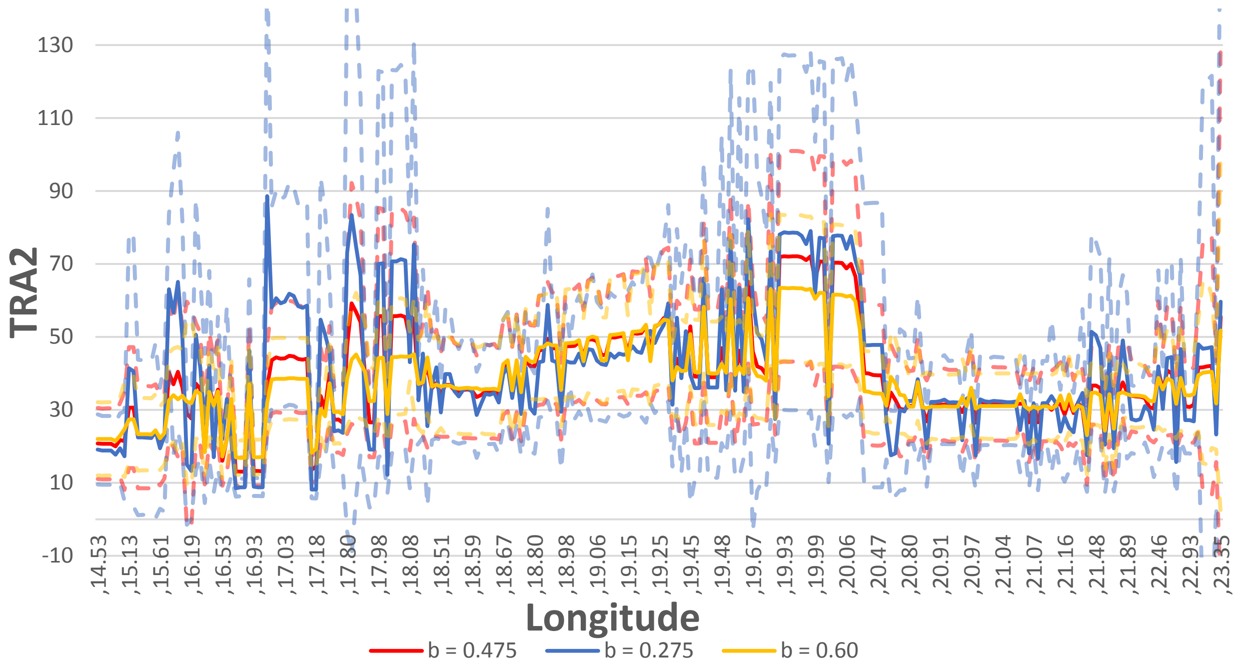
Figure A1. Parameters values with different bandwidths values plotted against longitude

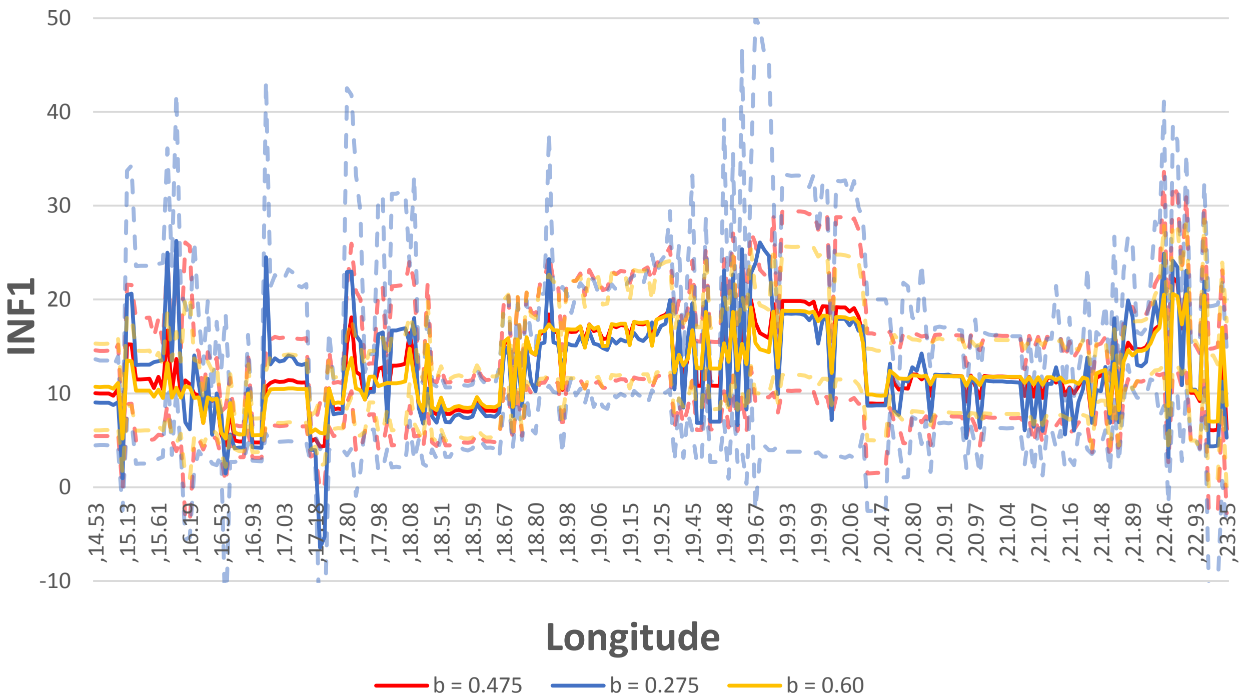


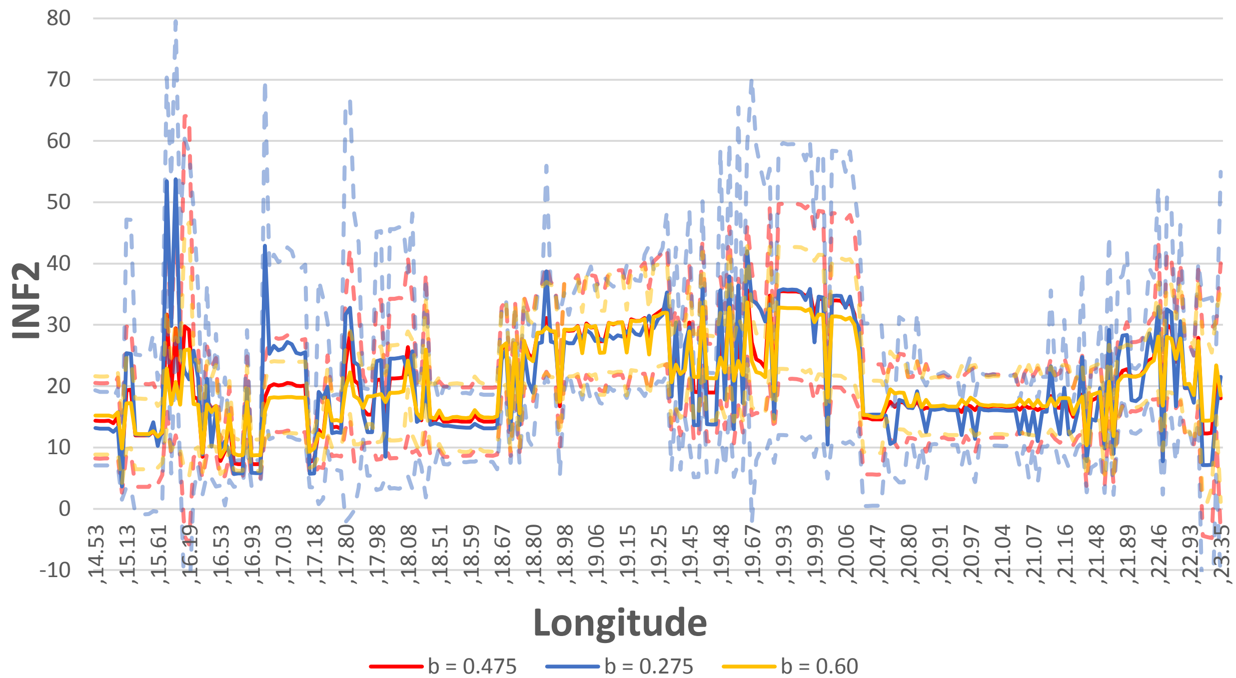


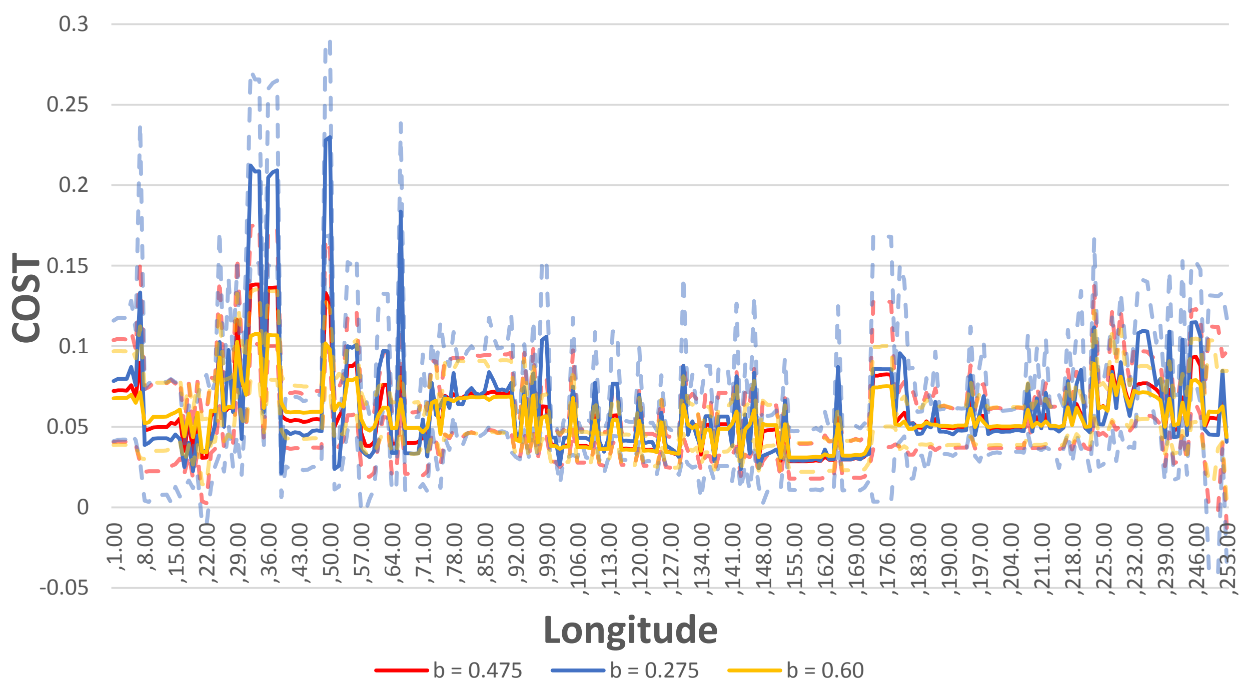

NAT2
110
90
70
50
30
10
-10
,14.53 ,15.13 ,15.61 ,16.19 ,16.53 ,16.93 ,17.03 ,17.18 ,17.80 ,17.98 ,18.08 ,18.51 ,18.59 ,18.67 ,18.80 ,18.98 ,19.06 ,19.15 ,19.25 ,19.45 ,19.48 ,19.67 ,19.93 ,19.99 ,20.06 ,20.47 ,20.80 ,20.91 ,20.97 ,21.04 ,21.07 ,21.16 ,21.48 ,21.89 ,22.46 ,22.93 ,23.35
Longitude
b = 0.475
b = 0.275
b = 0.60


TRA1
110
90
70
50
30
10
-10
,14.53 ,15.13 ,15.61 ,16.19 ,16.53 ,16.93 ,17.03 ,17.18 ,17.80 ,17.98 ,18.08 ,18.51 ,18.59 ,18.67 ,18.80 ,18.98 ,19.06 ,19.15 ,19.25 ,19.45 ,19.48 ,19.67 ,19.93 ,19.99 ,20.06 ,20.47 ,20.80 ,20.91 ,20.97 ,21.04 ,21.07 ,21.16 ,21.48 ,21.89 ,22.46 ,22.93 ,23.35
Longitude
b = 0.475
b = 0.275
b = 0.60


130
110
90
70
50
30
10
-10
TRA2
,14.53
,15.13
,15.61
,16.19
,16.53
,16.93
,17.03
,17.18
,17.80
,17.98
,18.08
,18.51
,18.59
,18.67
,18.80
,18.98
,19.06
,19.15
,19.25
,19.45
,19.48
,19.67
,19.93
,19.99
,20.06
,20.47
,20.80
,20.91
,20.97
,21.04
,21.07
,21.16
,21.48
,21.89
,22.46
,22.93
,23.35
Longitude
b = 0.475
b = 0.275
b = 0.60


50
40
30
20
10
0
-10
INF1
,14.53
,15.13
,15.61
,16.19
,16.53
,16.93
,17.03
,17.18
,17.80
,17.98
,18.08
,18.51
,18.59
,18.67
,18.80
,18.98
,19.06
,19.15
,19.25
,19.45
,19.48
,19.67
,19.93
,19.99
,20.06
,20.47
,20.80
,20.91
,20.97
,21.04
,21.07
,21.16
,21.48
,21.89
,22.46
,22.93
,23.35
Longitude
b = 0.475
b = 0.275
b = 0.60


INF2
Longitude
b = 0.475
b = 0.275
b = 0.60


COST
Longitude
b = 0.475
b = 0.275
b = 0.60

Appendix B. Results of regressions where the dependent variables are the absolute values of differences between WTP from GWMNL and location-specific MXL.

	SQ (alternative specific constant for the no-choice alternative)	***NAT*₁** (passive protection of most valuable forests – partial improvement)	***NAT*₂** (passive protection of most valuable forests – substantial improvement)	***TRA*₁** (the amount of litter in forests – partial improvement)	***TRA*₂** (the amount of litter in forests – substantial improvement)	***INF*₁** (tourist infrastructure – partial improvement)	***INF*₂** (tourist infrastructure – substantial improvement)
Constant	82.0358***	5.7755***	9.6175***	9.8597***	12.7036***	4.1844***	8.8477***
	(9.2459)	(1.5418)	(2.4648)	(2.6067)	(3.6717)	(1.0185)	(1.8850)
Area of coniferous forests	-0.4873**	0.0137	0.0114	0.0813	0.1330*	0.0176	0.0009
	(0.1989)	(0.0332)	(0.0530)	(0.0561)	(0.0790)	(0.0219)	(0.0405)
Area of deciduous forests	-1.2194*	0.3164***	0.4116**	0.2939	0.3938	0.1304*	0.2372*
	(0.6669)	(0.1112)	(0.1778)	(0.1880)	(0.2648)	(0.0735)	(0.1360)
Area of mixed forests	-0.6284	-0.0237	-0.0621	-0.0474	-0.0675	0.0244	-0.0575
	(0.4917)	(0.0820)	(0.1311)	(0.1386)	(0.1952)	(0.0542)	(0.1002)
Area of forests with age >120	-4.2394**	-0.9866***	-1.3444**	-2.4452***	-3.1542***	-1.1758***	-2.1505***
	(2.1335)	(0.3558)	(0.5688)	(0.6015)	(0.8473)	(0.2350)	(0.4350)
Average Euclidean distance to a forest	-11.0065***	0.4652	1.0371	-0.1832	0.3181	0.1845	-0.1190
	(3.4348)	(0.5728)	(0.9157)	(0.9684)	(1.3640)	(0.3784)	(0.7003)
Built-up area	0.3118***	0.0367*	0.0435	0.1361***	0.1378***	0.0221*	0.0455*
	(0.1208)	(0.0202)	(0.0322)	(0.0341)	(0.0480)	(0.0133)	(0.0246)
Area of forests with no. of species > 6	0.1275	0.1858**	0.2741**	0.4277***	0.6317***	0.1482***	0.3786***
	(0.4912)	(0.0819)	(0.1310)	(0.1385)	(0.1951)	(0.0541)	(0.1002)
No. of observations per location	-2.9135***	-0.4663***	-0.8032***	-0.5535***	-0.8810***	-0.1038	-0.3383**
	(0.7404)	(0.1235)	(0.1974)	(0.2088)	(0.2940)	(0.0816)	(0.1510)
Model characteristics							
R^2	18.19%	18.04%	16.58%	20.07%	17.08%	14.49%	18.11%
n (observations)	253	253	253	253	253	253	253
k (parameters)	9	9	9	9	9	9	9

*** p-value < 1%, ** p-value in [1%,5%), * p-value in [5%, 10%)