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SPATIAL HETEROGENEITY OF WILLINGNESS TO PAY FOR FOREST MANAGEMENT

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Spatial heterogeneity of willingness to pay for forest management

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Abstract

The paper investigates spatial heterogeneity of the public's preferences for the implementation of a new country-wide forest management and protection program in Poland. Spatial econometric methods and high resolution geographical information system (GIS) data related to forest characteristics are used to explain individual-specific willingness to pay (WTP) values, derived from a discrete choice experiment (DCE) study. We find that respondents' WTP is higher the closer they live to their nearest forest, and the scarcer forests are in the area where they live. Interestingly, the more highly ecologically valuable forests in respondents' area, the more they prefer extending areas of national forest protection. In addition, we investigate spatial patterns in individual-specific WTP scores and in latent class membership probabilities, finding that preferences are indeed spatially clustered. We argue that this clustering should be taken into account in both benefits analysis and policy-making.

Keywords:

discrete choice experiment, contingent valuation, willingness to pay, spatial heterogeneity of preferences, forest management, passive protection, litter, tourist infrastructure, mixed logit, Kriging, spatial-lag

JEL:

Q23, Q28, I38, Q51, Q57, Q58

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1. Introduction

There is now compelling evidence that preferences for some environmental goods follow spatial patterns. One reason for this is that there are differences in spatial configuration of these goods – so that preferences adapt to individuals' environments ([Nielsen *et al.*, 2007](#)) and the availability of substitutes ([Munro and Hanley, 1999](#)). Another line of reasoning concerns residential sorting: people's preferences for environmental goods 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](#)). Recent developments in Geographical Information Systems (GIS) allow the researcher to obtain rich datasets containing detailed information about the spatial configuration of environmental goods, and to investigate spatial patterns in stated and revealed preferences for such environmental goods. In this paper we use GIS data related to forest characteristics in Poland as variables explaining the variation in the public's Willingness To Pay (WTP) for changes in forest attributes resulting from the implementation of a new country-wide forest management and protection program. Individual-specific WTP values are derived from a Discrete Choice Experiment (DCE) study. Spatial regression methods are used to investigate the relationships between stated WTP for changes in national forest management, and the characteristics of forests where people live. This shows that WTP is higher the closer people live to their nearest forest, but WTP is also higher the scarcer forests are in the area where they live (that is, the lower is the fraction of forest cover to total land area). We also investigate spatial patterns in latent classes which represent heterogeneity in preferences, finding that such latent clusters of preferences in space do indeed exist. Identifying such clusters, we argue, is useful for policy-making and environmental management.

The literature devoted to spatial dependencies in economic values includes revealed preference studies where GIS data are used to identify characteristics of environmental goods. For example, [Schläpfer and Hanley \(2003\)](#) use this approach to investigate preferences for landscape protection programs, and [Termansen *et al.* \(2008\)](#) investigate recreational values of forests in Denmark using site choice data for 52 forest sites whose characteristics (forest area, share of coniferous forests and distance to the site) are described using GIS data. Spatial-referenced environmental data has also been used extensively in stated-preference studies. For example, [Jørgensen *et al.* \(2013\)](#) use GIS data on distance to the Odense River as an explanatory variable in contingent valuation study. GIS data is also used in the development of benefits transfer models based on stated preference data (e.g., [Bateman *et al.*, 2011](#)). More relevant for this paper are studies where GIS data has been used to investigate the spatial distribution of WTP derived from DCE studies. Examples of this approach include non-parametric analysis of respondents' WTP for choice attributes. [Campbell *et al.* \(2008\)](#) applied Moran's *I* statistic and confirmed significant global spatial clustering of the WTP estimates and that these estimates exhibited positive spatial

autocorrelation even over relatively large spatial areas. In a follow-up paper, [Campbell et al. \(2009\)](#) find further evidence of an intrinsic spatial influence on WTP. They used Kriging methods as a means of benefit transfer to illustrate spatial variation and regional disparities in WTP. As a further example, [Johnston et al. \(2011\)](#) use the Getis-Ord statistic to locate welfare hot-spots.

Parametric analysis of estimated WTP was applied by [Abildtrup et al. \(2013\)](#) and [Yao et al. \(2014\)](#). In both of these studies of forest values, random effect panel models were used with socio-demographic and spatial data as explanatory variables to explain variation in individual WTP values for changes in forest management. In [Abildtrup et al. \(2013\)](#), spatial heterogeneity in WTP for forest attributes (tree species, facilities, hiking paths and access to water) was modeled using binary variables equal to one if a forest with corresponding attributes was within 10 km radius from an individuals' home. Choice data came from an internet sample of residents in Lorraine, in Northern France, and concerned enhancements in the recreational resources of local forests. Similarly, [Yao et al. \(2014\)](#) used data on forest size and distance from respondent's homes to capture spatial dependencies in WTP for enhancement of biodiversity forests in New Zealand. Five different indicators of forest biodiversity were used, all of them representing abundance of threatened species. Finally [Broch et al. \(2013\)](#) included spatial variables as covariates directly in the DCE model.

The main objective of our paper is to identify spatial determinants and spatial clustering of WTP for forest attributes in Poland, since any such spatial variability has implications for the design and acceptability of forest management policies. To do this we apply a two stage analysis: firstly we estimate a Mixed Logit (MXL) model using the public's DCE responses to derive individual WTP values, while in the second stage we use these individual-specific WTP estimates as dependent variables in a GIS-based spatial regression. This two-stage approach very much follows that of [Abildtrup et al. \(2013\)](#) and [\(Yao et al., 2014\)](#). However, our paper extends the existing literature of spatial heterogeneity of preferences in three ways. Firstly our GIS dataset contains much more detailed information about forest characteristics than any of the earlier approaches. Secondly, for the second stage of the analysis, spatial econometric models were applied which provide more reliable results than ordinary regression. Thirdly, we apply a spatial latent class analysis to identify clusters of respondents with similar preferences for forest conservation. This proves to be a useful exercise in revealing spatial patterns of values.

2. Methodology

The analysis conducted in this paper is divided into three stages. First, an Mixed Logit (MXL) model is estimated which allows the estimation of individual-specific WTP using sample-level WTP distribution parameters, respondents' choices and Bayes theorem. In the second stage these WTP scores are modeled

in a spatial econometric framework using GIS data as explanatory variables. In the third stage, spatial latent class models are estimated, and results are mapped.

2.1. First stage – the MXL model

Stated preferences methods have several advantages over revealed preferences methods, but the most important in the context of estimating values for forest attributes is that the experimental design process avoids some of the multi-colinearity problems with respect to forest attributes which result from using travel cost approaches to study the same problem ([Hanley et al., 2003](#)).

In this paper we apply the mixed logit model (MXL). It is a very flexible model which allows for heterogeneity in respondents' preferences. The model is defined as follows. A respondent n 's utility from choosing alternative i in the j -th choice task is given by:

$$U_{ijn} = V_{ijn} + \varepsilon_{ijn} = \beta_n' \mathbf{X}_{ijn} + \varepsilon_{ijn}, \quad (1)$$

where the error term ε_{ijn} is assumed to be i.i.d with a Gumbel distribution. β_n is an individual set of parameters which are assumed to come from some known distribution which depends on some unknown parameters θ to be estimated (usually means, and the covariance matrix). In most cases the researcher is interested in the estimation of the distribution of WTP, therefore it is useful to re-parametrize equation (1) to:

$$U_{ijn} = -\beta_n^{\text{cost}} \left(-\frac{\beta_n^{\text{non-cost}}}{\beta_n^{\text{cost}}} \mathbf{X}_{ijn}^{\text{non-cost}} - X_{ijn}^{\text{cost}} \right) + \varepsilon_{ijn} = -\beta_n^{\text{cost}} \left(\alpha_n' \mathbf{X}_{ijn}^{\text{non-cost}} - X_{ijn}^{\text{cost}} \right) + \varepsilon_{ijn}, \quad (1)$$

where α_n is vector of WTPs for every non-monetary attribute defined as $-\beta_n^{\text{non-cost}} / \beta_n^{\text{cost}}$. This specification is often referred to as a WTP-space model, in which rather than assuming some distribution for the β_n vector, the distribution of vector $(\alpha_n, \beta_n^{\text{cost}})$ is assumed and the associated parameters estimated. In this case the likelihood of the n 'th respondent's choices (y_n) is given by:¹

$$L(y_n | \mathbf{X}_n, \theta) = \iint_{\alpha_n, \beta_n^{\text{cost}}} \prod_j \sum_i y_{ijn} \frac{\exp(V_{ijn})}{\sum_k \exp(V_{kjn})} f(\alpha_n, \beta_n^{\text{cost}} | \theta) d\alpha_n d\beta_n^{\text{cost}}. \quad (2)$$

¹ $f(\alpha_n, \beta_n^{\text{cost}} | \theta)$ is a joint density function.

The likelihood function is integrated over random parameters as they are not directly observed in the data. This integral is usually approximated using pseudo-random numbers (in this paper 10,000 scrambled Sobol draws were used).²

As random parameters are not observed one cannot obtain them directly, but it is possible to derive their conditional expected values using Bayes Theorem, resulting in:

$$E(\mathbf{a}_n | y_n, \mathbf{X}_n, \theta) = \int \mathbf{a}_n \frac{p(y_n | \mathbf{X}_n, \theta, \mathbf{a}_n, \beta_n^{\text{cost}}) f(\mathbf{a}_n, \beta_n^{\text{cost}} | \theta)}{p(y_n | \mathbf{X}_n, \theta)} d(\mathbf{a}_n, \beta_n^{\text{cost}}), \quad (3)$$

which can also be simulated using numerical methods as well. These so called ‘WTP scores’ will be used in the second stage of our analysis.³

Following [Campbell et al. \(2009\)](#), we also provide a visual representation of spatial distribution of WTP-scores using regression Kriging. Specifically, we estimated linear regression models with the dependent variable being a WTP-score and an independent variable being a 2-D smooth spline function of latitude and longitude. Using splines allowed us to capture nonlinear spatial dependencies in probability scores. Having estimates of this model we then extrapolate results onto the whole map. Calculations were done using the R *mgcv* package ([Wood and Wood, 2007](#)).

2.2. Second stage – the spatial regression model

In this stage the WTP scores calculated in stage 1 are explained using GIS data on forest characteristics and survey data on respondents’ socio-demographic variables. The most common approach currently applied in the literature (e.g., [Campbell, 2007](#); [Yao et al., 2014](#)) is the random effects panel regression in which all WTP scores are modeled simultaneously. This approach, however, forces some unrealistic assumptions on the modelling process, such as all variables influence every WTP score in the same way. A possible solution is to interact the variables in the model with dummy variables for every WTP score ([Campbell, 2007](#)), but this may result in too many parameters to estimate. For these reasons we estimated a separate model for each WTP score. A spatial lag model was applied⁴, where each WTP is assumed to be of the following form:

² See [Garrido \(2003\)](#) and [Munger et al. \(2012\)](#) for further details on the use of Sobol draws in MXL models.

³ While disregarding the fact that these conditional parameters themselves follow a random distribution around this mean, this approach nevertheless gives us some information about the most likely position of a respondent on the distribution.

⁴ The decision to use a spatial lag model, as opposed to a spatial error model, is based on our belief that there is potential for diffusion and WTP feedbacks effects; and that this effect could be more profound than accounting for the variables omitted from the systematic component which could induce spatial correlation in the errors of the

$$WTP = \tau c + \rho \mathbf{W}' \mathbf{W} TP + \gamma' \mathbf{Z} + e. \quad (4)$$

In this specification, c is a constant, $\mathbf{Z}$ is a matrix of GIS and socio-demographic explanatory variables and γ is a vector of parameters to be estimated (which can be different for every WTP score). The error term e is assumed to follow a normal distribution with zero mean and standard deviation σ . Additionally, a spatial lag term is included which addresses the problem of possible spatial autocorrelation between observations which is not explained by the covariates. $\mathbf{W}$ is a matrix of spatial weights and ρ is a scalar parameter which corresponds to the magnitude of this spatial correlation – high positive values of ρ can be interpreted as showing that the WTP values of respondents who live close to each other are more similar than the covariates would predict. The inverse square function of distance was chosen for the spatial weights. This allows us to capture global effects, as it has non-zero weights even for very far away regions, but gives much higher weights for very close regions, thus allowing us to capture so-called hot-spot effects.

2.3. Spatial latent class analysis

Finally, to provide an additional insight by visualizing the clustering of WTPs, we estimated a latent class logit (LC) model, applied Bayes theorem to predict each individual's probability of participating in each latent class, and lastly extrapolated these probability scores using regression Kriging.

Formally, individual i 's utility (in WTP-space) for the LC model can be written down in a similar way to the MXL model (1):

$$U_{ijn}^c = -\beta_c^{\text{cost}} (\alpha_c' \mathbf{X}_{ijn}^{\text{non-cost}} - X_{ijn}^{\text{cost}}) + \varepsilon_{ijn} = V_{ijn}^c + \varepsilon_{ijn}. \quad (5)$$

The only difference is that now utility is also indexed by the class to which a respondent belongs ($c \in \{1, \dots, C\}$) and parameters are not individual-specific but rather class-specific. As in reality we have no way of knowing for sure which class an individual belongs to, this leads to a formula on the likelihood of class membership of the following form:

$$L(y_n | \mathbf{X}_n, \theta) = \sum_c \pi_c L_c(y_n | X_n, \theta_c), \quad (6)$$

where $L_c(y_n | X_n, \theta_c)$ is a likelihood conditional on being in class c :

$$L_c(y_n | X_n, \theta_c) = \prod_j \sum_i y_{ijn} \frac{\exp(V_{ijn}^c)}{\sum_k \exp(V_{kjin}^c)}, \quad (7)$$

and π_c is a set of parameters representing probability of being in given class to be estimated with restriction that $\sum_c \pi_c = 1$. After estimation of the model, individual n 's probability score of being in class c can be estimated with Bayes' formula:

$$p_{cn} = \frac{L_c(y_n | X_n, \theta_c) \pi_c}{L(y_n | X_n, \theta)}. \quad (8)$$

Therefore it is a likelihood conditioned on being in class c , multiplied by the probability of being in this class, divided by an unconditional likelihood.

As a final step, we extrapolated the conditional probability scores. For extrapolation we used once again the regression Kriging method, but this time we used logit regressions with dependent variable $\phi_{cn} = \mathbf{I}\{p_{cn} > 0.5\}$ and a 2-D smooth spline function of latitude and longitude as an independent variable.

3. Data

3.1. Discrete Choice Experiment

The dataset used in this study was investigated in [Czajkowski *et al.* \(2014a\)](#) and [Czajkowski *et al.* \(2014b\)](#). The original survey was conducted in 2010 on a representative sample of 1001 Polish adults. The main objective of the survey was to find the most important biodiversity and recreation attributes of Polish forests for the general public. After intensive qualitative studies, three attributes were selected to describe the environmental management options for national forests, namely: (1) protection of the most ecologically valuable forests in Poland, (2) reducing the amount of litter (garbage, rubbish) in forests and (3) increasing the level of recreational infrastructure, such as way-marking of trails. In all cases, respondents were asked whether they would support a particular policy change for the environmental management of all publicly-owned forests in Poland, which currently comprise 82% of all forests in Poland.

In Poland about 3% of all 90,000 km² of forests are perceived as the most ecologically valuable. Currently only about half of these forests are properly protected which led to the following levels of the first attribute being chosen:

**Status quo**

Passive protection of 50% of the most ecologically valuable forests
(1.5% of all forests area)

**Partial improvement**

Passive protection of 75% of the most ecologically valuable forests
(2.25% of all forests area)

**Substantial improvement**

Passive protection of 100% of the most ecologically valuable forests
(3% of all forests area)

For the second attribute, the amount of litter in forests was used, since this is a significant problem in Poland. It is obvious that littering can decrease the recreational value of forests as well as non-use values. For this attitude the following levels were chosen:

**Status quo**

No changes in amount of litter

**Partial improvement**

Decrease amount of litter in forests of about 50%

**Substantial improvement**

Decrease amount of litter in forests of about 90%

Pre-testing showed that availability of the appropriate infrastructure for tourists is important for a forest's recreational value. This infrastructure may include parking spaces, paths and trails for tourists, picnic sites etc. Levels for this attribute were chosen as:



Status quo
No changes in infrastructure



Partial improvement
Appropriate tourist infrastructure in an additional 50% of forests



Substantial improvement
Appropriate tourist infrastructure available in twice as many (100 % more) forests

The last attribute was the annual cost of these changes in the form of an increase in annual income taxes to pay for a national program of enhanced forest management. The levels we used were: 0, 10, 25, 50 and 100 PLN.

Every respondent completed 26 choice tasks⁵ with 4 alternatives. In every choice task a Status Quo alternative with no changes in each attribute and a zero additional tax cost was included. An example choice card is provided as Figure 1. For more details about design and survey see [Czajkowski *et al.* \(2014a\)](#).

⁵ The preference stability and learning or fatigue effects in the course of the 26 choice tasks are analysed in [Czajkowski *et al.* \(2014b\)](#).

Figure 1. An example choice card used in the DCE study (translation)

	Alternative 1	Alternative 2	Alternative 3	Alternative 4
Protection of ecologically valuable forests	 Status quo Passive protection of 50% of the most ecologically valuable forests (1.5% of all forests)	 Status quo Passive protection of 50% of the most ecologically valuable forests (1.5% of all forests)	 Status quo Passive protection of 50% of the most ecologically valuable forests (1.5% of all forests)	 Substantial improvement Passive protection of 100% of the most ecologically valuable forests (3% of all forests, 100% increase)
Litter in forests	 Status quo No change in the amount of litter in the forests	 Partial improvement Decrease the amount of litter in the forests by half (50% reduction)	 Status quo No change in the amount of litter in the forests	 Partial improvement Decrease the amount of litter in the forests by half (50% reduction)
Infrastructure	 Status quo No change in tourist infrastructure	 Status quo No change in tourist infrastructure	 Partial improvement Appropriate tourist infrastructure in an additional 50% of the forests (50% increase)	 Substantial improvement Appropriate tourist infrastructure available in twice as many forests (100% increase)
Cost	0 PLN	10 PLN	25 PLN	100 PLN
Your choice	☐	☐	☐	☐

3.2. GIS data

Information on forest characteristics used in this study was obtained from two different sources which we will now describe. 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.⁶ 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 we used was the Polish Information

⁶ See <http://www.eea.europa.eu/publications/COR0-landcover> for further information on the CORINE programme.

System of State Forests which has been used in Poland for the management of State Forests since 1995. This tool contains very precise data about the characteristics of forests in Poland.

The data from these sources were available for 10x10 km squares. In total, 3307 such squares cover the 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 places 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

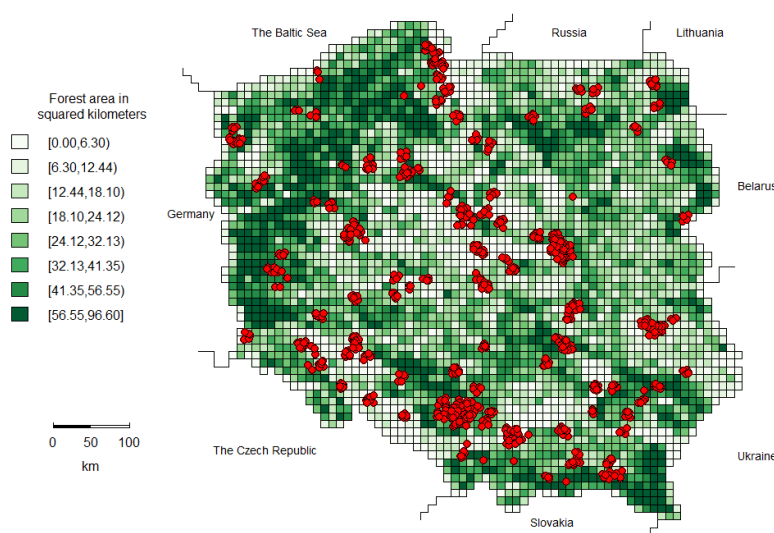


Table 1. GIS variables used to characterize the locations in which respondents' lived

Variable name	Description	Source
Area of coniferous forests	Sum of areas of all coniferous forests [km ²]	Corine Land Cover
Area of deciduous forests	Sum of areas of all deciduous forests [km ²]	Corine Land Cover
Area of mixed forests	Sum of areas of all mixed forests [km ²]	Corine Land Cover
Average Euclidean distance to forest	It is average distance from any point in 10x10 km square to the nearest forest	Corine Land Cover
Area of forests with age > 120	Sum of areas of all forests older than 120 years [km ²]	Information System of State Forests
Area of forests with no. of species > 6	Sum of areas of all forests with no. of tree species greater than 6 [km ²]	Information System of State Forests
Built-up area	Built-up area [km ²]	Corine Land Cover

Maps presenting the distribution of the environmental characteristics of forests used in this paper are presented in Appendix 1. Note that in the results section we investigate an alternative categorization of forest cover, which uses a continuous variable for forest area in a grid square, and dummy variables for whether this is mainly deciduous or mainly coniferous. We also tried using dummies to represent forest areas. None of these alternative ways of representing the area and type of forest in a grid square produced a change in our conclusions.

4. Results

4.1. Discrete Choice Model

The MXL model was estimated in Matlab.⁷ 10,000 scrambled Sobol draws were used to simulate the Maximum Likelihood function ([Czajkowski and Budziński, 2015](#)). The model was estimated in WTP space. For every non-monetary attribute, two dummy variables were included to allow for varying marginal utilities associated with their improvements. As a result *NAT*, *TRA* and *INF* represent partial or substantial improvement in passive protection of most ecologically valuable forests, the amount of litter, and recreation infrastructure respectively. In addition, the status quo dummy (*SQ*) was included in the utility function as an alternative specific constant for the “no new improvements” option. The cost parameter was assumed to have a negative log-normal distribution, while other parameters were assumed normally distributed. Full correlation of parameters was allowed. The results are presented in Table 2.

⁷ The dataset and software used for this analysis are available at <http://czaj.org/> and provided under [CC BY 4.0 license](#).

Table 2. Mixed Logit results of the discrete choice experiment dealing with changes in management of Polish forests (model in WTP-space, results in EUR per year⁸)

Variable	Mean		Std. Dev.	
	coef.	st. err.	coef.	st. err
NAT₁ (passive protection of most valuable forests – partial improvement)	9.8917***	(0.3436)	11.8622***	(0.5881)
NAT₂ (passive protection of most valuable forests – substantial improvement)	13.5450***	(0.4791)	17.3510***	(0.8286)
TRA₁ (the amount of litter in forests – partial improvement)	11.5526***	(0.3746)	12.8895***	(0.6352)
TRA₂ (the amount of litter in forests – substantial improvement)	17.6876***	(0.5818)	21.4890***	(0.9262)
INF₁ (tourist infrastructure – partial improvement)	6.2377***	(0.2740)	6.1410***	(0.3710)
INF₂ (tourist infrastructure – substantial improvement)	8.6357***	(0.3161)	8.6104***	(0.4837)
SQ (alternative specific constant for the no-choice alternative)	-13.7474***	(0.9304)	30.9090***	(1.7497)
COST⁹ (annual cost – tax increase)	-1.5776***	(0.0338)	1.0971***	(0.0400)
Model characteristics				
Log-likelihood (constant only)	-36,045.3765			
Log-likelihood	-17,169.7628			
McFadden's pseudo-R ²	0.5236			
AIC/n	1.3228			
n (observations)	26,026			
k (parameters)	44			

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

All of the MXL parameters are highly significant. The Status Quo coefficient is negative, which means that on average individuals derive utility from improvements in forest ecosystem management. However, this effect varies considerably in the sample as indicated by a relatively high standard deviation estimate. The WTP for all non-monetary attributes have positive means and vary significantly. Consistent with economic theory, higher levels of attributes have higher means. The highest mean WTP is associated with reduction in the amount of litter in forests – respondents were willing to pay about 12 EUR annually for 50% reduction of litter in forests and about 18 EUR for a 90% reduction. This is about 4 EUR more than average WTP for passive protection of all the most ecologically valuable forests and 9 EUR more than for 100% increase in the appropriate tourist infrastructure. Appendix 2. presents the

⁸ At 1 PLN ≈ 0.25 EUR ≈ 0.33 USD.

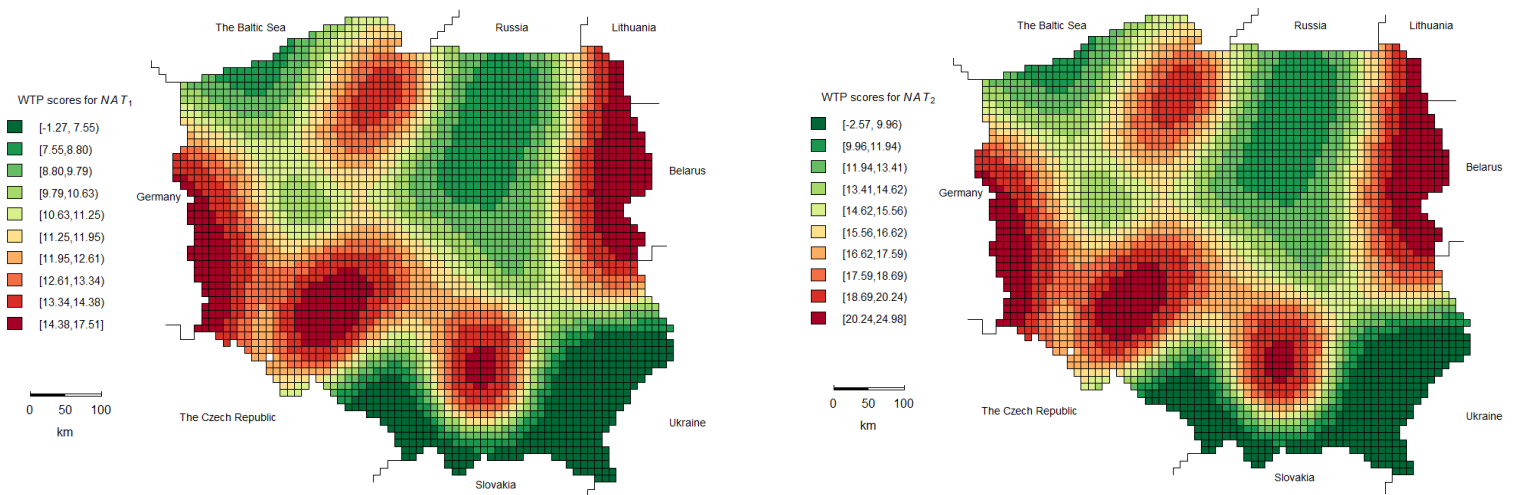
⁹ Underlying normal random variable parameters of the preference-space equivalent of *COST* are reported.

correlation matrix of WTP's estimated by the MXL model and correlation matrix of predicted WTP scores. Note that there is an almost perfect correlation between attribute levels of each attribute – we return to this observation when interpreting the results of spatial regression models.

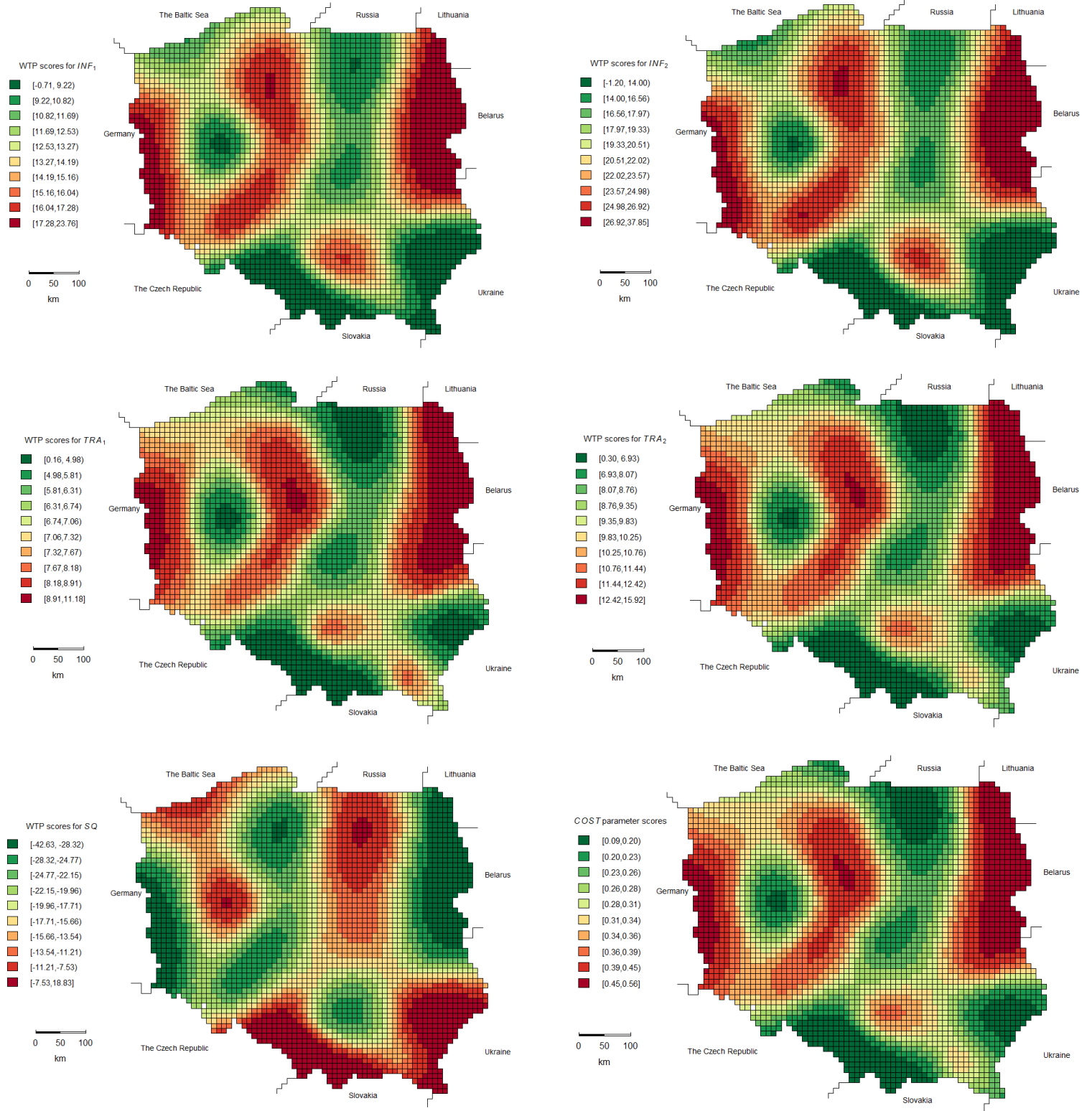
4.2. Spatial heterogeneity of respondents' preferences

To investigate the influence of various characteristics of the location in which respondents live (grid cell characteristics) on their preferences, individual WTP scores were predicted using Bayes theorem.¹⁰ To facilitate interpretation, analysis of these scores started with extrapolating them to the map of Poland using the regression Kriging method. The results are presented in Figure 3, where each of the 8 panels represents distribution of WTP scores associated with one of the discrete choice attributes. Two things can be noted right away – a strong spatial correlation of WTP-scores and a clear similarity of respondents' spatial preferences for 'partial' and 'substantial' improvements of each attribute. In addition, one can observe relatively stronger preferences for all improvements in the eastern, western and parts of central Poland, while they are the least appreciated in the south-east (the Bieszczady region), the north-east (the Mazury region) and north-west (the Pomorze region). Respondents from different regions also differ with respect to how important each attribute is (how much they would be WTP for them), although these dissimilarities are less stark.

Figure 3. Spatial distribution of respondents' WTP scores associated with each of the choice attributes



¹⁰ Whilst we recognize that these conditional (individual-specific) estimates themselves follow a distribution, we use the means of these distributions for each respondent as it indicates their 'most likely' WTP value.



To more formally test if there are spatial correlations we apply a simple OLS regression for each of the attribute levels. Residuals from each of these regressions illustrate the significance and the extent of spatial autocorrelation. Moran's I statistics are presented in Table 3. These results illustrate that there is

positive global spatial autocorrelation in the residuals from every regression. This means that the variables do not correctly capture the spatial dependencies in WTP scores, and that more advanced spatial models should be applied.

Table 3. Moran's I statistics for residuals from the OLS regression on respondents' marginal WTP

	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)
Moran's I statistic	0.1364	0.1406	0.2410	0.2393	0.2217	0.2087
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

In order to discover what drives these spatial differences in respondents' WTP we use a spatial lag model. In addition to local forest characteristics, we include socio-demographic variables, namely: respondent's age, a dummy showing if the respondent has a bachelor or Master's degree, gender, number of household members and income.¹¹ Insignificant variables (p-value > 10%) were then excluded from the model to increase efficiency of the other coefficients' estimates. Models were estimated using the R statistical software using *spdep* package ([Bivand, 2005](#)). Results are provided in Table 4.

¹¹ Since many respondents did not report their income in the survey the variable used as an income proxy was the question "How would you rate the financial situation of your household?" measured on 5 point Likert scale with 1="Bad" and 5 = "Good". We made sure the results are robust with respect to using other measures of respondents' income (mean income in the area, unemployment rate, percentage population employed, population density, build-up area).

Table 4. Spatial lag models results for the effects of land use patterns on WTP for different forest conservation attributes.

	<i>NAT</i> ₁	<i>NAT</i> ₂	<i>TRA</i> ₁	<i>TRA</i> ₂	<i>INF</i> ₁	<i>INF</i> ₂
	(passive protection of most valuable forests – partial improvement)	(passive protection of most valuable forests – substantial improvement)	(the amount of litter in forests – partial improvement)	(the amount of litter in forests – substantial improvement)	(tourist infrastructure – partial improvement)	(tourist infrastructure – substantial improvement)
Constant	14.9043*** (2.0156)	21.0248*** (2.9433)	5.1349*** (0.8522)	7.4821*** (1.2240)	13.2227*** (2.1499)	21.3849*** (3.5729)
Area of coniferous forests	-0.0846*** (0.0282)	-0.1239*** (0.0413)	-	-	-0.0760** (0.0300)	-0.1349*** (0.0501)
Area of deciduous forests	-0.4702*** (0.0931)	-0.6914*** (0.1366)	-0.1211*** (0.0404)	-0.1929*** (0.0582)	-0.4368*** (0.0992)	-0.7444*** (0.1656)
Area of mixed forests	-0.2848*** (0.0682)	-0.4184*** (0.1000)	-0.0868*** (0.0313)	-0.1348*** (0.0451)	-0.2697*** (0.0728)	-0.4541*** (0.1214)
Area of forests with age >120	1.3470*** (0.3118)	1.9699*** (0.4571)	0.3036** (0.1401)	0.4950** (0.2016)	1.1797*** (0.3317)	2.0481*** (0.5540)
Average euclidean distance to forest	-2.1218*** (0.4822)	-3.1376*** (0.7071)	-0.5427*** (0.1902)	-0.8298*** (0.2736)	-2.0968*** (0.5148)	-3.5062*** (0.8590)
Age	-0.0824*** (0.0191)	-0.1210*** (0.0280)	-0.0216** (0.0090)	-0.0351*** (0.0129)	-0.0585*** (0.0204)	-0.0940*** (0.0340)
Higher education	-	-	-0.6453* (0.3403)	-0.9342* (0.4893)	-	-
Income	1.0972*** (0.3081)	1.6240*** (0.4516)	0.5170*** (0.1473)	0.7710*** (0.2118)	1.1743*** (0.3287)	1.9320*** (0.5485)
ρ	0.2071*** (0.0397)	0.2134*** (0.0396)	0.3712*** (0.0356)	0.3672*** (0.0357)	0.3437*** (0.0364)	0.3267*** (0.0369)
Models characteristics						
Log-likelihood (constant only)	-3,721.467	-4,106.124	-2,992.612	-3,358.061	-3,817.743	-4,324.178
Log-likelihood	-3,665.362	-4,048.631	-2,919.451	-3,282.389	-3,740.727	-4,251.617
McFadden's pseudo-R ²	0.0151	0.0140	0.0244	0.0225	0.0202	0.0168
AIC/n	7.3406	8.1066	5.8455	6.5702	7.4894	8.5112
<i>n</i> (observations)	1001	1001	1001	1001	1001	1001
<i>k</i> (parameters)	10	10	10	10	10	10

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

In all 6 models the spatial lag parameter ρ is positive and highly significant – indicating that respondents are expected to have higher WTP values if, on average, their neighbors have high WTP values. The results of the models estimated for different levels of the same attribute are similar. This is not surprising as their correlation is quite large (cf. Appendix 2). We interpret and discuss these results in section 4.4.

Finally, to investigate if our specification captured all spatial dependencies in WTP scores, Moran's *I* test on residuals was applied again. The results, provided in Table 5, show that our spatial lag models have addressed the problem of unexplained spatial dependencies between observations (the remaining spatial dependencies are not significant, and the associated *p*-values are very high).

Table 5. Moran's I statistics for residuals from spatial lag models

	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)
Moran's I statistic	0.0004	0.0001	-0.0168	-0.0153	-0.0089	-0.0075
p-value	0.4754	0.4801	0.7547	0.7338	0.6351	0.6112

4.3. Latent classes and spatial clustering

It is quite likely that people with similar stated preferences are found in spatial clusters (as already shown in the mapped WTP distributions). This is for the two reasons noted in the introduction: amenities may attract specific kinds of people (specific in terms of their tastes) to locate in areas which score relatively highly in certain environmental features such as the area, proximity or type of woodland; or living in an area with a given environmental character results in individuals' preferences evolving to a set which shows a preference for the environmental features where they live. Of course, spatial patterns in socio-economic variables such as incomes also exist, and to the extent that these socio-economic variables drive WTP, this will also result in a clustering of WTP values.

Figures 4a and 4b show the spatial clusters from the latent class analysis for 2- and 3- class models, respectively. Model results are given in Table 6.

As can be seen from the model with 2 classes, about 75% of respondents are likely to belong to the first class. This class is more pro-environmental in the sense that their WTP for changes in forest management are much higher than WTP indicated by the utility function parameters for the second latent class, whilst the SQ parameter is negative. In the LC model with 3 classes, about 66% of respondents is likely to belong to the third class, which is even more pro-environmental than Class 1 in the previous model. WTP's in classes 1 and 2 are much lower and also the SQ coefficients are highly positive. Especially in class 1 WTP for not making any change is higher than the sum of WTPs for making substantial improvements in all three attributes together. Class 1 can therefore be interpreted as respondents who in every situation would prefer not to make any improvements to national forest management, while class 2 respondents would derive some utility from changes in forest management, but this would not be substantial.

Table 6. Results of 2- and 3- class Latent Class models

	LC – 2 classes		LC – 3 classes		
	Class 1	Class 2	Class 1	Class 2	Class 3
NAT₁ (passive protection of most valuable forests – partial improvement)	12.3493*** (0.2905)	2.6718*** (0.3737)	6.0982** (2.4286)	3.6140*** (0.2430)	15.4226*** (0.4215)
NAT₂ (passive protection of most valuable forests – substantial improvement)	18.3199*** (0.3365)	3.0398*** (0.4200)	5.4206** (2.4889)	4.3648*** (0.2365)	23.5171*** (0.5800)
TRA₁ (the amount of litter in forests – partial improvement)	17.4802*** (0.3884)	4.3709*** (0.5068)	3.7034 (2.2862)	4.4229*** (0.2619)	22.3024*** (0.6425)
TRA₂ (the amount of litter in forests – substantial improvement)	26.1813*** (0.4503)	5.4522*** (0.4886)	7.1491** (2.9177)	6.3993*** (0.2330)	33.4739*** (0.8011)
INF₁ (tourist infrastructure – partial improvement)	8.2853*** (0.2926)	2.6689*** (0.4479)	5.0444** (2.4213)	2.9540*** (0.2434)	9.7624*** (0.3962)
INF₂ (tourist infrastructure – substantial improvement)	12.1895*** (0.3176)	3.7445*** (0.4291)	5.0295** (2.2527)	3.4621*** (0.2051)	15.4939*** (0.5144)
SQ (alternative specific constant for the no-choice alternative)	-3.6316*** (0.4677)	12.7028*** (0.7026)	45.3237*** (7.4730)	0.8621*** (0.2505)	-14.6239*** (0.8892)
COST (annual cost – tax increase (preference-space equivalent))	0.0900*** (0.0014)	0.2278*** (0.0057)	0.1036*** (0.0115)	0.2677*** (0.0032)	0.0732*** (0.0017)
π	0.7449	0.2551	0.1808	0.1623	0.6569

Models characteristics

Log-likelihood (constant only)	-36,045.3765	-36,045.3765
Log-likelihood	-20,973.9519	-19,156.0679
McFadden's pseudo-R ²	0.4181	0.4686
AIC/n	1.6131	1.4741
n (observations)	26026	26026
k (parameters)	17	26

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

Firstly, we present Moran's I statistics for calculated probability scores in Table 7. In all cases, the *p*-values are very low allowing us to conclude that there is a very significant spatial dependence.

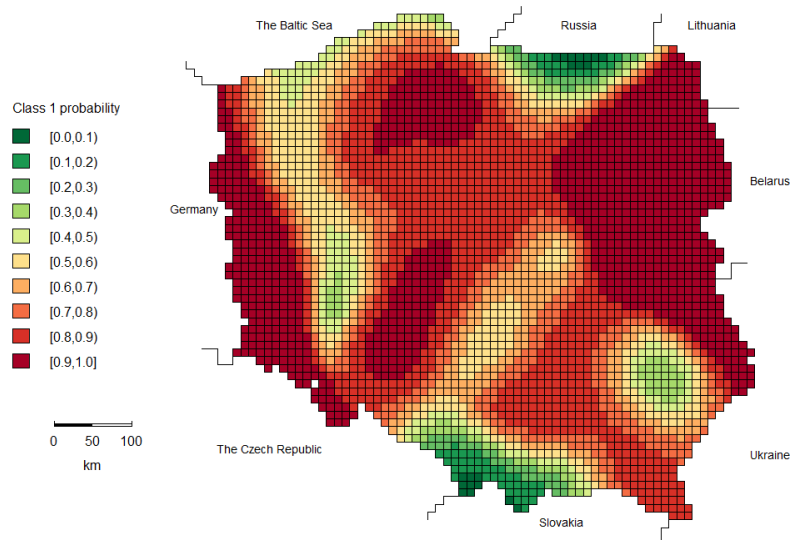
Table 7. Moran's I statistics for class probability scores

	LC - 2 classes		LC - 3 classes		
Moran's I statistic	0.2595	0.2595	0.2468	0.1902	0.2675
p-value	0.0000	0.0000	0.0000	0.0000	0.0000

Figure 4a illustrates the spatial distribution of extrapolated probability scores of belonging to class 1 for the 2-class LC model.¹² This is thus a spatial representation of clustering in WTP values for forest enhancements. It appears that individuals who have low probability scores (and therefore are more likely to belong to class 2, which values the changes in forest management less) are mostly located in the northeast (near the border with Russia) and also found in the south of Poland, near the borders with Slovakia and the Czech Republic. Other regions with lower probabilities include patches of central regions, particularly between some of the big cities. We note, however, that there were not many observations in our sample which were located there (cf. Figure 1.), it is therefore possible that this is an artefact of extrapolating low probability scores in the bigger cities mentioned. The highest probability scores are placed near west and east borders and also in the central Poland. These are the regions which have relatively fewer forests. This result thus supports our findings reported earlier in this paper.

¹² We do not provide a similar map for second class, as it would be the same map with reversed colors.

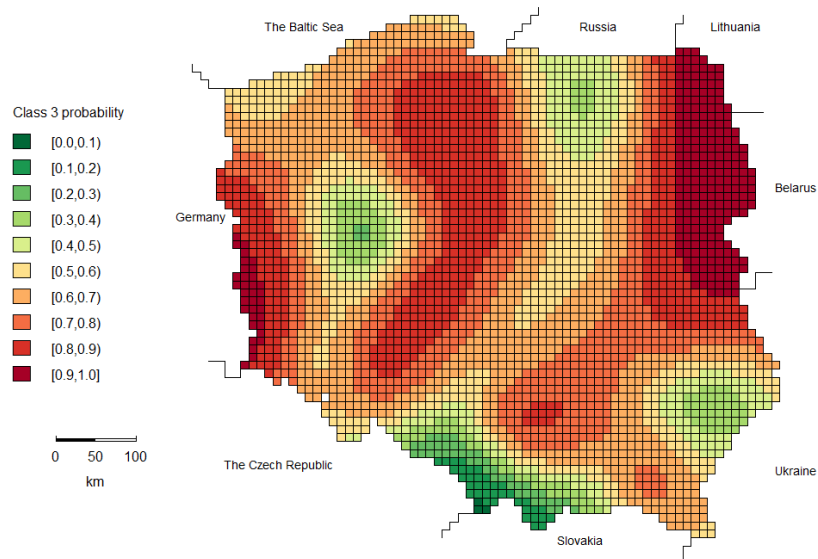
Figure 4a. Extrapolated probability of being in class 1 (for LC model with 2 classes)



In Figure 4b. we report similar maps for case of the LC model with 3 classes. The conclusions from the distribution of the probability of belonging to class 3 (the most pro-environmental respondents) are very similar to those derived from the model with 2 classes for the most pro-forest-conservation group. The regions of high probability are significantly smaller because the probabilities are around 10 percentage points lower than for the case with 2-class model. The main insight of the LC with 3 classes is that one can now see that individuals from class one (who do not want any changes) are mostly concentrated in the northern part of Poland (near the border with Russia) and in the south (near the borders with Slovakia and the Czech Republic). People with lower WTP are also more likely to live near big cities (albeit the effect is less evident). Lastly, class 2 probability seems to be the highest around the city of Poznań in central Poland, and also (albeit to a lesser extent) in the south (near the border with the Czech Republic) and north-east (near the border with Russia).

Figure 4b. Extrapolated class membership probability (for the LC model with 3 classes)





5. Discussion and conclusions

The most consistent results to emerge from the spatial lag models are that (i) the further away from a forest one lives, the less he or she is willing to pay for improvements to national environmental forest management; and (ii) the more forests there are in the 10 x 10 km square where one lives, the less he or she is willing to pay for enhancing the national forest estate. Result (i) is a type of distance decay function found in many papers in the literature (e.g., [Jørgensen et al., 2013](#)). Result (ii) initially looks counter-intuitive, but also makes sense. Recall that the discrete choice experiment asks respondents to bid for increases in the quality of environmental management of forests nationally. The more of a good that is available to the respondent, the lower his or her marginal WTP for increases in that good. That is exactly what we find here. Another explanation might be that two of the improvements included in the choice experiment (littering and recreational facilities) might lead to increases in visitor pressures in an area where forests are currently more abundant. This increased congestion and traffic etc. might be a source of dis-utility to local people, who are more likely to experience such effects the greater is the area of forest in the grid square where they live.

Looking at the type of forest growing in the grid square where respondents live, the “type dummy” specification shows that having a predominance of conifer species always lowers WTP, whilst having a predominance of deciduous trees in your local forests increases WTP for improvements to national forest environmental management. This echoes early hedonic price analysis of the impacts of forest characteristics on property values in the UK ([Garrod and Willis, 1992](#)).

The presence of forests older than 120 years in the area where the respondent lives has a positive and highly significant effect on their WTP for conserving natural forests and removing litter, and for

improving forest infrastructure. Forests of this age are about 5% of all forests in Poland and are considered the most ecologically valuable. The coefficients of this variable are also much higher (in absolute values) than coefficients of the other forest-related area characteristics. It thus seems that individuals who live near old-growth forests have substantially different preferences with respect to the desirability of enhancements in national forest management and protection practices.

Finally, we note that GIS variables indicating the area of built-up land and the area of forests with more than 6 tree species did not turn out to be significant. As for socio-demographic variables considered, we found that age had a highly significant and negative effect on WTP while income has a positive influence on WTP. We also found that respondents' with higher education levels were WTP less for the improvements in the infrastructure than the remainder of the sample.

The spatial patterns of WTP for environmental improvements provide important information for improving the economic efficiency of land management. Combined with information on the spatial distribution of costs, such WTP data enables the better targeting of environmental management, since those areas with higher net benefits can become the focus for enhancements, given limited budgets for funding such improvements. In this paper, we combine detailed spatial data on forest characteristics and land use patterns with estimates of individual WTP (obtained from mixed logit models) for changes in forest management, using spatial statistical methods to deal with problems of autocorrelation. We also use latent class modelling, and show that there are spatial clusters of people with similar preferences for environmental improvements in different parts of Poland. As far as the authors are aware, this paper is the first to combine these modelling approaches, and thus the paper will be of general interest to those concerned with relating spatial patterns of land use and land management with environmental valuation estimates.

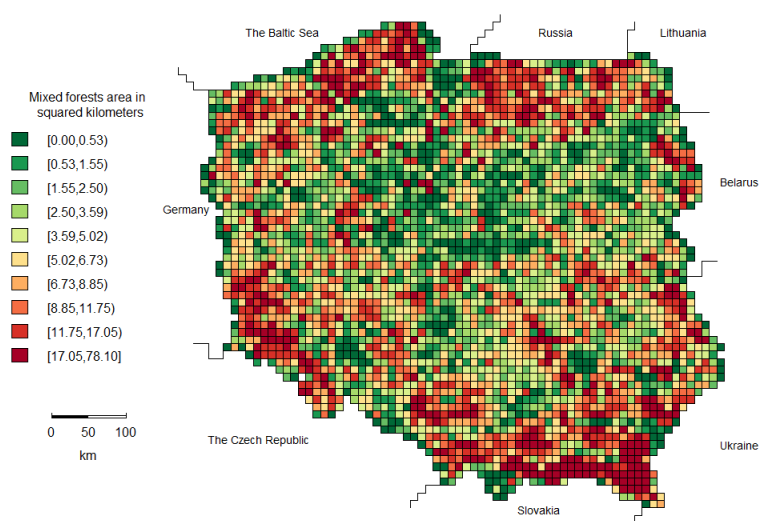
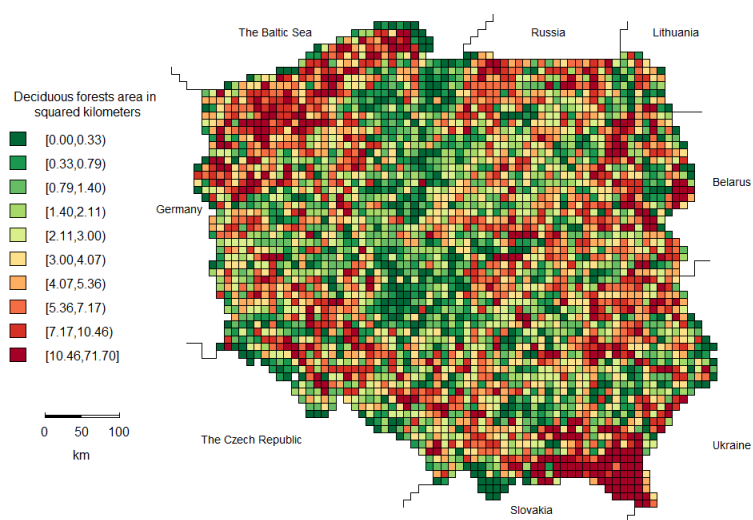
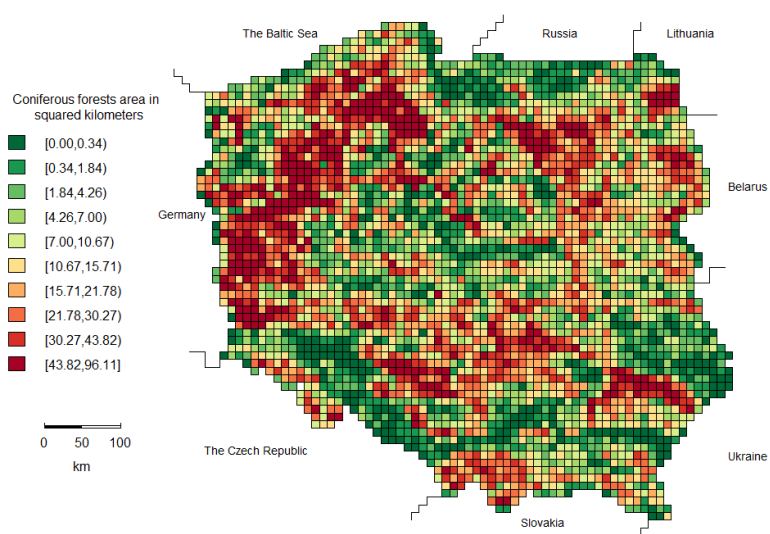
What our data cannot address is the question of *why* there are spatial clusters of preferences. One possible reason is the equilibrium sorting view of individuals choosing where to live based on their preferences and the amenities of an area. An alternative view is that it is the environmental characteristics of an area which shape the preferences of those who live there. Some kind of quasi-experiment would be needed to parse between these competing explanations.

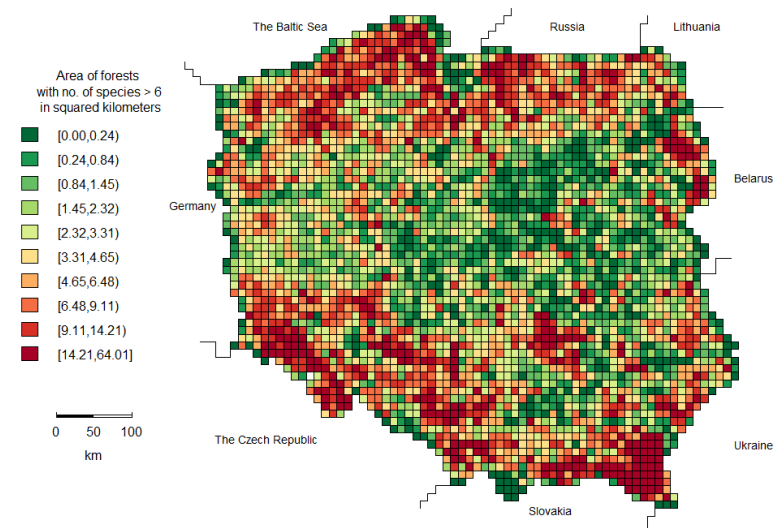
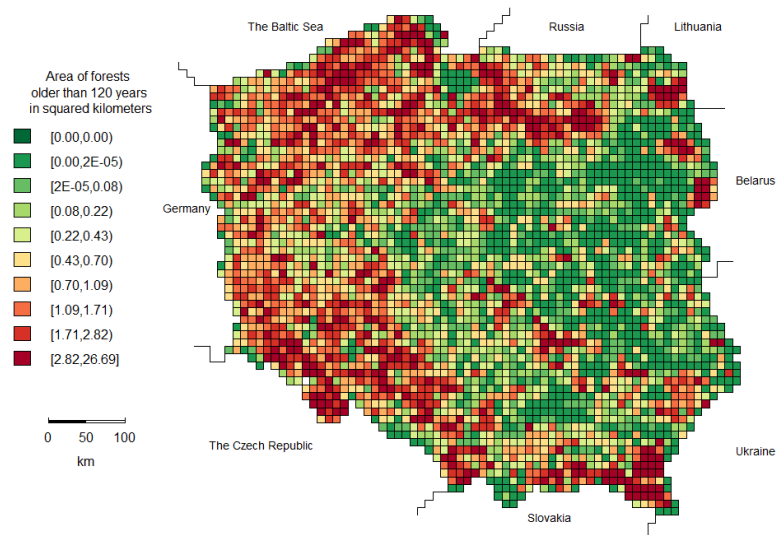
References

- Abildtrup, J., Garcia, S., Olsen, S. B., and Stenger, A., 2013. Spatial preference heterogeneity in forest recreation. *Ecological Economics*, 92(1):67-77.
- Bateman, I. J., Brouwer, R., Ferrini, S., Schaafsma, M., Barton, D. N., Dubgaard, A., Hasler, B., Hime, S., Liekens, I., Navrud, S., De Nocker, L., Ščeponavičiūtė, R., and Semėnienė, D., 2011. Making Benefit Transfers Work: Deriving and Testing Principles for Value Transfers for Similar and Dissimilar Sites Using a Case Study of the Non-Market Benefits of Water Quality Improvements Across Europe. *Environmental and Resource Economics*, 50(3):365-387.
- Bivand, R., 2005. The spdep package. Comprehensive R Archive Network, Version 0.3-13.
- Broch, S. W., Strange, N., Jacobsen, J. B., and Wilson, K. A., 2013. Farmers' willingness to provide ecosystem services and effects of their spatial distribution. *Ecological Economics*, 92(0):78-86.
- Campbell, D., 2007. Willingness to Pay for Rural Landscape Improvements: Combining Mixed Logit and Random-Effects Models. *Journal of Agricultural Economics*, 58(3):467-483.
- Campbell, D., Hutchinson, G., and Scarpa, R., 2009. Using choice experiments to explore the spatial distribution of willingness to pay for rural landscape improvements. *Environment and Planning A*, 41(1):97-111.
- Campbell, D., Scarpa, R., and 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.
- Czajkowski, M., Bartczak, A., Giergiczny, M., Navrud, S., and Żylicz, T., 2014a. Providing Preference-Based Support for Forest Ecosystem Service Management. *Forest Policy and Economics*, 39:1-12.
- Czajkowski, M., and Budziński, W. (2015). "An insight into the numerical simulation bias – a comparison of efficiency and performance of different types of quasi Monte Carlo simulation methods under a wide range of experimental conditions." In: *Environmental Choice Modelling Conference*, Copenhagen.
- Czajkowski, M., Giergiczny, M., and Greene, W. H., 2014b. Learning and fatigue effects revisited. Investigating the effects of accounting for unobservable preference and scale heterogeneity. *Land Economics*, 90(2):323-350.
- Garrido, R. A., 2003. Estimation performance of low discrepancy sequences in stated preferences. 10th International Conference on Travel Behaviour Research.
- Garrod, G., and Willis, K., 1992. The amenity value of woodland in Great Britain: A comparison of economic estimates. *Environmental and Resource Economics*, 2(4):415-434.
- Hanley, N., Shaw, W. D., and Wright, R. E., eds. 2003. *The New Economics of Outdoor Recreation*. Edward Elgar Pub.
- Johnston, R. J., Ramachandran, M., Schultz, E. T., Segerson, K., and Besedin, E. Y., 2011. Characterizing spatial pattern in ecosystem service values when distance decay doesn't apply: choice experiments and local indicators of spatial association. Paper number 103374 provided by Agricultural and Applied Economics Association in its series 2011 Annual Meeting, July 24-26, 2011, Pittsburgh, Pennsylvania.
- Jørgensen, S. L., Olsen, S. B., Ladenburg, J., Martinsen, L., Svenningsen, S. R., and 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(0):58-66.
- Munger, D., L'Ecuyer, P., Bastin, F., Cirillo, C., and Tuffin, B., 2012. Estimation of the mixed logit likelihood function by randomized quasi-Monte Carlo. *Transportation Research Part B: Methodological*, 46(2):305-320.
- Munro, A., and Hanley, N., 1999. Information, Uncertainty and Contingent Valuation. In: *Contingent Valuation of Environmental Preferences: Assessing Theory and Practice in the USA, Europe, and Developing Countries*, I. J. Bateman and K. G. Willis, eds., Oxford University Press.

- Nielsen, A. B., Olsen, S. B., and Lundhede, T., 2007. An Economic Valuation of the Recreational Benefits Associated with Nature-Based Forest Management Practices. *Landscape and Urban Planning*, 80:63-71.
- Schläpfer, F., and Hanley, N., 2003. Do Local Landscape Patterns Affect the Demand for Landscape Amenities Protection? *Journal of Agricultural Economics*, 54(1):21-34.
- Termansen, M., Zandersen, M., and McClean, C. J., 2008. Spatial substitution patterns in forest recreation. *Regional Science and Urban Economics*, 38(1):81-97.
- Timmins, C., and 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.
- Wood, S., and Wood, M. S., 2007. The mgcv package. www.r-project.org.
- Yao, R. T., Scarpa, R., Turner, J. A., Barnard, T. D., Rose, J. M., Palma, J. H. N., and Harrison, D. R., 2014. Valuing biodiversity enhancement in New Zealand's planted forests: Socioeconomic and spatial determinants of willingness-to-pay. *Ecological Economics*, 98(0):90-101.

Appendix 1. Distribution of the environmental characteristics of forests in Poland





Appendix 2. Analysis of correlations between respondents WTP

Table A2.1 Correlation matrix of WTP's estimated by Mixed Logit

	<i>NAT₁</i>	<i>NAT₂</i>	<i>TRA₁</i>	<i>TRA₂</i>	<i>INF₁</i>	<i>INF₂</i>	<i>SQ</i>	<i>COST</i>
<i>NAT₁</i>	1.0000	0.9995	0.7419	0.7478	0.4952	0.5892	-0.7501	-0.6211
<i>NAT₂</i>	0.9995	1.0000	0.7520	0.7553	0.5134	0.6048	-0.7681	-0.6290
<i>TRA₁</i>	0.7419	0.7520	1.0000	0.9894	0.8282	0.8742	-0.9136	-0.7770
<i>TRA₂</i>	0.7478	0.7553	0.9894	1.0000	0.7424	0.8078	-0.8955	-0.7526
<i>INF₁</i>	0.4952	0.5134	0.8282	0.7424	1.0000	0.9722	-0.7651	-0.7161
<i>INF₂</i>	0.5892	0.6048	0.8742	0.8078	0.9722	1.0000	-0.8100	-0.7651
<i>SQ</i>	-0.7501	-0.7681	-0.9136	-0.8955	-0.7651	-0.8100	1.0000	0.6917
<i>COST</i>	-0.6211	-0.6290	-0.7770	-0.7526	-0.7161	-0.7651	0.6917	1.0000

Table A2.2 Correlation matrix of predicted WTP scores

	<i>NAT₁</i>	<i>NAT₂</i>	<i>TRA₁</i>	<i>TRA₂</i>	<i>INF₁</i>	<i>INF₂</i>	<i>SQ</i>	<i>COST</i>
<i>NAT₁</i>	1.0000	0.9997	0.7944	0.7977	0.6118	0.6840	-0.8335	-0.6539
<i>NAT₂</i>	0.9997	1.0000	0.8033	0.8051	0.6267	0.6973	-0.8445	-0.6610
<i>TRA₁</i>	0.7944	0.8033	1.0000	0.9945	0.8907	0.9261	-0.9677	-0.7895
<i>TRA₂</i>	0.7977	0.8051	0.9945	1.0000	0.8401	0.8841	-0.9566	-0.7730
<i>INF₁</i>	0.6118	0.6267	0.8907	0.8401	1.0000	0.9913	-0.8680	-0.7574
<i>INF₂</i>	0.6840	0.6973	0.9261	0.8841	0.9913	1.0000	-0.9033	-0.7908
<i>SQ</i>	-0.8335	-0.8445	-0.9677	-0.9566	-0.8680	-0.9033	1.0000	0.7520
<i>COST</i>	-0.6539	-0.6610	-0.7895	-0.7730	-0.7574	-0.7908	0.7520	1.0000



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